UTILIZING MULTI-SOURCE ABUNDANCE ESTIMATION AND CLIMATE VARIABILITY TO FORECAST PACIFIC SALMON POPULATIONS

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Abstract

Data limitation is a common property of many fisheries. Some Pacific salmon populations are a typical example of this situation because the monitoring of numerous tributaries within an area becomes logistically intractable. Fishery management often responds to this scenario with qualitative stock assessments in the form of harvest projections. In some cases, fishery data, although limited, exists in a variety of sources and may be integrated to develop quantitative population estimates. The first objective of this investigation is to generate a modeling process that combines multiple data sources to estimate abundance and escapement estimates for data-limited salmon populations. Second, we consider the reliability of these estimates by testing for robustness to various simulated levels of measurement error in the data. Finally, we perform rigorous development and selection on an age structured spawner-recruit model that incorporates abundance and escapement estimates and identifies potential environment-recruit relationships.

We demonstrate our technique with a case study on summer chum salmon from the Kuskokwim and Yukon Rivers, Alaska. Recent declines of summer chum returns to this salmon-dependent region have created hardships for the local area residents. We developed a maximum likelihood statistical framework that synchronously combined all available data sources from this management region to estimate abundance and escapement. Successful estimation was dependent on an independent estimate of abundance for a least a few years. We provide error estimates of the modeling process through bootstrap methods. Simulations showed that measurement error had negligible effect on abundance estimates, whereas performance for escapement estimation was tied to the sequence of abundance years.

High explanatory power was attained by including environmental variables in the spawner-recruit relationship developed from these population estimates. We used a three-stage modeling process to maintain biological realism in the predictor variables. Recent changes in variables chosen for the best model were consistent with poor environmental conditions and estimates of forecasting error were much lower than models using no environmental information. Based on our findings, we recommend that managers consider the utility of multiple source estimation and environmental variability with our modeling approach for future regulatory decisions of Pacific salmon fisheries in data-limited regions.

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Dedication

A long while ago my Olde' Bub said to me, "Lo que mucho abarca poca aprieta." At the time, the words confused me, yet as I reflected upon my choices that led to the completion of this endeavor, I understood what he meant. Though this tome may seem a product of unfathomable ambition, I kept on keeping on because my family embraced my decisions with positive guidance. They hoped for me, they prayed for me, and they helped me to try. I could not have done this without them. The Lord walks with me, listening with infinite patience and I now stand at the edge of a new adventure.

For my mom and dad who always knew I could,

For my Dana who found a way to help me smile,

For my Tutu who braved the cold to see her flower,

For my brothers who taught me how to laugh,

For my Tante' who thought enough to ask,

For my Bub who was here all along,

For my 'Ohana, mahalo nui loa.

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General Introduction

Population data in many fisheries are often insufficient to develop adequate estimates for conventional assessment methods. This data limitation is typical of new and developing fisheries where sampling difficulties arise from the practical constraints of a large geographic region or small local economy. Fisheries managers are still responsible for developing appropriate regulations even when traditional estimates are poor or unavailable. Often the response is to generate qualitative assessments in the form of harvest outlooks or informal projections. These measures are unfortunately limited in scope and predictive ability. To produce a reliable quantitative forecast for a given region, estimates of abundance or other population parameters are necessary (Hilborn and Walters 1992). New applications must be developed to utilize the available fishery information in a forecasting procedure suited to the system conditions.

In some cases, fishery information, although limited, exists from a variety of sources. If these multiple sources were used in concert, adequate population estimates might be attainable. Once developed, these estimates may be combined with appropriate predictor information in a forecasting model specific to the region of interest. Our objectives in this study are to 1) generate a statistical framework that combines multiple data sources to estimate population abundance, 2) consider the reliability of these estimates by testing robustness to assumptions within the methodology, and 3) use rigorous model development to identify meaningful predictor variables, increase understanding of the system, and improve forecasting.

We restricted our investigation to semelparous populations in data-limited situations. Individuals that survive to maturity in this type of population each make at most a single reproductive contribution; therefore, only the spawner-recruit relationship is required to describe the dynamics of the population (Quinn and Deriso, 1999). This type of population is less complex and well-suited for applying novel methods on data-limited areas. Pacific salmon (*Oncorhynchus sp.*) represent a group of semelparous species with many examples of data-limited populations.

Our methodologies were tested on a case study of summer chum salmon (*O. keta*) in the Kuskokwim and Yukon Rivers, Alaska. In this situation, the escapement data were limiting as monitoring of all streams within this system is intractable for logistical reasons. Our approach to sparse escapement data was to apply principal components analysis (PCA) to available time series, and use the extracted common pattern as our escapement index. Following this, we combined all available fishery data sources in a maximum likelihood statistical framework to produce estimates of abundance and escapement. We then evaluated the assumptions of our model by simulating various levels of measurement error on a salmon population where abundance and escapement were known. Finally, we formulated a three-stage model development process that focused on biological realism to forecast Kuskokwim and Yukon River summer chum. We used rigorous model selection to gain an understanding of the spawner-recruit dynamics within this region and identify potential environment-recruit relationships.

1 Estimating Indices of Abundance and Escapement of Pacific Salmon for Data-Limited Situations [1]

1.1 Abstract

We demonstrate the process of simultaneously combining multiple sources of available fishery information to estimate total abundance in data-limited situations. The application is specific to semelparous populations, such as Pacific salmon, where only spawner and recruit data is necessary to describe the dynamics of these populations. We apply this technique to summer chum salmon of the Kuskokwim and Yukon Rivers of Alaska. Since 1997, low numbers of returning chum salmon to these rivers have resulted in low harvests and significant negative economic and social impacts to rural residents of the region. The existing salmon stock assessment programs in these river basins are inadequate for conventional estimates of total run abundance and modeling of stock dynamics.

Our approach was to apply principal components analysis (PCA) to estimate the underlying common trend in escapement. We then combined this index with other available fishery data in a maximum likelihood statistical framework, weighting the data sets according to their quality. Data sources included commercial catch and effort, escapement surveys, test fishery catch rates and whole-river sonar counts. This methodology produced indices of chum salmon total abundance and escapement for the

[1] Authors: S. Kalei Shotwell and Milo D. Adkison, Journal: Transactions of the American Fisheries Society. Scheduled for printing in May 2004 issue.

Kuskokwim and Yukon Rivers. Error estimates of this time series and model parameters were generated by bootstrap methods. The essential feature in these estimates is that the pattern over time varies more than the error estimates and does appear to contain a recognizable trajectory. We also found that several parameters of the model were confounded without some independent measure of total abundance or escapement. Therefore, whole-river sonar was essential in this model. The first principal component from PCA contained 51% of the variability in the tributary escapements and loadings were all positive and equally weighted. This indicated that the escapement trend estimated by PCA was consistent over a large geographic area, suggesting survival was predominantly influenced by conditions where the fish share a common environment. We recommend that this framework be adapted to other regions and different semelparous species under similar data-limited situations. Managers using the method should fully understand the limitations of the model due to our assumptions on fixed scaling constants and weighting schemes as well as potential influence of substantial measurement error in the data sources incorporated in our approach.

1.2 Introduction

Fisheries are often considered data-limited when essential fish information is lacking for conventional assessment methods. This situation is characteristic of new and developing fisheries where there is initially little biological data and when the practical constraints of a large geographic management region or a small local economy limit the collection of data. Managers must still respond and make the necessary decisions on appropriate regulations for these fisheries. Often this results in qualitative assessments in the form of harvest outlooks or informal projections that are limited in scope and predictive capability. New applications that provide a quantitative assessment of population dynamics in data-limited regions are necessary to statistically describe a fishery and aid managers in future regulatory decisions. In some cases, fishery information, although limited, exists in a variety of sources. If these sources were used in concert, adequate estimates of abundance or other population estimates might be attainable.

We developed a maximum likelihood statistical model for combining multiple data sources on semelparous populations in data-limited situations. Individuals that survive to maturity in a semelparous population each make a single reproductive contribution; therefore, only the spawner-recruit relationship is required to describe the dynamics of the population (Quinn and Deriso, 1999). This type of population is less complex and well-suited for applying novel methods in data-limited cases because only total abundance (recruits) and escapement (spawners) are necessary to construct the basis of such a relationship. Pacific salmon represent a group of semelparous species and several populations reside in data-limited areas. In this case, the escapement data is often the limiting factor in a stock-recruitment analysis as monitoring of multiple streams within a given system often becomes intractable for logistical reasons. Our approach to sparse escapement data was to utilize the pattern extraction qualities of principal components analysis (PCA) to derive an escapement index from available time series. In this way, we preserved the trend of escapement in our analysis. The index was then combined with other available data on the population in a maximum likelihood framework to estimate total abundance and escapement. We demonstrate the application of this process to semelparous populations with a case study on summer chum salmon (*Oncorhynchus keta*) in the Kuskokwim and Yukon Rivers, Alaska.

1.2.1 Case Study History

Chum salmon are the most highly utilized species among the six salmon species produced by Alaska's Kuskokwim and Yukon Rivers (Figures 1.1 & 1.2). The annual returns of mature adults support important subsistence and commercial fisheries for rural area residents. From 1980 to 1996, the average annual chum salmon harvest in these two rivers was 1.94 million fish (Burkey et al. 2002, JTC 2002). That average, however, dropped to 0.32 million fish for the years 1997 to 2001, and was generally coupled with low chum salmon escapements in the few tributary streams that are monitored (Burkey et al. 2001, JTC 2002). This recent downturn in chum salmon abundance, and the consequent reduction in commercial harvest, prompted the governor of the State of Alaska to issue formal declarations of economic disaster for the region in 1997, 1998, 2000 and 2001. The Alaska Board of Fisheries declared Kuskokwim and Yukon River chum salmon populations to be "stocks of concern" in September 2000 (Alaska Department of Fish and Game 2000, Burkey et al. 2000). For residents of the region, circumstances were further aggravated by a reduction in the market value of the chum salmon (Buklis 1999; Eggers 2002). The low harvests coupled with the decreased economic value of this resource have resulted in significant negative social and economic impacts in many rural communities along the Kuskokwim and Yukon Rivers.

The primary management objective for chum salmon along these river systems is to ensure adequate spawning escapements (Burkey et al. 2001, JTC 2002). Currently, the Alaska Department of Fish and Game (ADFG) produces informal run outlooks for the Kuskokwim and Yukon Rivers based on piece-meal combinations of subsistence reports, test-fish catches, commercial catch statistics, main stem sonar, and tributary escapement projects such as aerial surveys, counting towers, weirs, and tributary sonar projects (Burkey et al. 2001, Bergstrom et al. 2001, Geiger and McNair 2001). The Kuskokwim and Yukon Rivers, however, are large and complex systems, and the existing salmon stock assessment programs are inadequate for conventional estimates of escapement and total run size (Burkey et al. 2001, Bergstrom et al. 2001). Escapement goals are, therefore, mostly set in accordance with historical escapement levels (Buklis 1993). Two early run chum salmon stocks in the Yukon River basin have recently had escapement goals developed based on spawner-recruit relationships; however, these analyses rely on broad assumptions about stock composition in the commercial harvest (Clark 2001 and Clark and Sandone 2001).

Our study objective is to estimate past escapement and total returns to the Kuskokwim and Yukon Rivers to improve management tools. The first step is to consider the usefulness of the available information on chum returns. We hypothesize that, when combined, historical time series of commercial catch and effort data, test fisheries, and indices of spawner abundance in various tributaries contain enough information to reconstruct the abundance of chum returns and escapement to the Kuskokwim and Yukon River drainages with a useful level of accuracy. Based on these data, a stock-recruitment relationship could then be estimated to develop forecasts that utilize possible relationships between the environment and chum production. Incorporating this information into the local management of the fishery would allow for more efficient use of this resource and improve conservation efforts.

1.3 Methods

In any one river system, chum salmon often exist as two genetically distinct groups that can be distinguished by differences in their run timing (early and late) (Salo 1991). In this study we concentrate on the early run of chum salmon to the Kuskokwim and Yukon Rivers. These early run chum salmon are more abundant and smaller in size than later chum runs and typically more historical data is collected on the early run (Burkey et al. 2001, Bergstrom et al. 2001). The early run population of chum salmon begins to enter the Kuskokwim River from the sea in early June, with numbers peaking in early July and diminishing through early August (Molyneaux 1998). In the Yukon River, the early run population (referred to as "summer chum") enters freshwater beginning in mid-June, peaks in late June to early July, and diminishes through late July (T. Lingnau and D. Molyneaux, Alaska Dept. of Fish and Game, personal communication). Summer chum spawning primarily occurs in the lower 500 miles of the Yukon River drainage and also in the Tanana River drainage (Bergstrom et al. 2001).

1.3.1 Data Used

The Kuskokwim and Yukon Rivers are within the fisheries management region described by ADFG Commercial Fisheries Division as the Arctic-Yukon-Kuskokwim Region (Region 3). Primary sources for the information used in this study (Table 1.1) were the Kuskokwim and Yukon Area Annual Management Reports (AMRs) produced by ADFG Division of Commercial Fisheries.

1.3.1.1 Tributary Escapements

Salmon spawning escapements are estimated for selected tributaries of the Kuskokwim and Yukon River drainages through various sonar, weir, tower, and aerial survey projects (Burkey et al. 2001, Bergstrom et al. 2001). The most complete of these datasets extends back to 1976 for the Kuskokwim River, and to 1975 for the Yukon River (Table 1.1).

1.3.1.2 Subsistence Harvest

Subsistence harvest of chum salmon occurs throughout most of both the Kuskokwim and Yukon River drainages, but harvest is most intense along approximately the lower third of the mainstem of each river (Burkey et al. 2002, Borba and Hamner 2001). Annual subsistence harvest data collected through voluntary reporting programs is summarized in the AMRs (Burkey et al. 2001, Bergstrom et al. 2001). In the Kuskokwim River, subsistence harvest apportioned specifically to chum salmon is only available since about 1985 (Table 1.1). Non-apportioned data exists prior to 1985, consisting mainly of chum salmon lumped with small numbers of sockeye and pink salmon. The majority of salmon that were not chum in the non-apportioned years were thought to consist mainly of sockeye salmon (D. Molyneaux, Alaska Dept. of Fish and Game, personal communication) and sockeye subsistence harvest is available for the apportioned years since 1985. Kuskokwim chum salmon subsistence harvest has been steadily decreasing since 1971, most likely due to the lower demand owing to decreased use of dog teams for transportation (Francisco et al. 1988; Burkey et al. 2001). However, subsistence harvests of sockeye salmon have stayed relatively constant over this period. We considered the average of sockeye subsistence harvest over the apportioned years to adequately represent the amount of salmon that were not chum in the non-apportioned years (Burkey et al. 2001). We, therefore, subtracted this value from the non-apportioned data to estimate chum salmon subsistence harvests from 1976 to 1984. In the Yukon, subsistence harvest was not recorded over all districts until 1977 (Table 1.1). There was a resurgence of subsistence harvest from 1974 to the late 1980s due to the legal sale of subsistence salmon roe and renewed interest in recreational use and racing of sled dogs (Borba and Hamner 2001). Average subsistence harvest did not begin steadily decreasing until 1989 (JTC 2002). Thus, we used the average subsistence harvest of chum salmon from 1977 through 1989 as a proxy for the missing Yukon subsistence chum harvest data for 1975 and 1976.

1.3.1.3 Commercial Catch

The commercial chum salmon fishery of the Kuskokwim River is limited to the lower third of the mainstem (Burkey et al. 2002). In the Yukon River, commercial fishing occurs throughout most of the mainstem, but most of the early chum harvest occurs in the lower third of the river (Bergstrom et al. 2001). For both the Kuskokwim and Yukon Rivers, the reach of river where commercial fishing occurs is divided into segments; Districts W-1 and W-2 for the Kuskokwim River and Districts Y-1 through Y-6 for the Yukon River. Catch is reported by the district in which it was taken. Within the fishing season, summer chum salmon are harvested during both unrestricted and restricted openings. Unrestricted openings are typically fished with 8½-inch mesh nets and occur during the beginning of the season when fishers are targeting chinook salmon. Openings that are designated as "restricted" allow fishing with 5½-inch mesh nets. These periods typically occur after the chinook season and fishers target chum salmon.

We summarized commercial catch data in two forms: annual (Figures 1.3a & 1.3b) and weekly catch by river (Table 1.1). The weekly commercial catch statistics are the sum of the individual fishing periods for a given week, defined as Sunday through Saturday. A summary of the historical commercial catches by fishing period was available in the 2000 Kuskokwim Area AMR (Burkey et al. 2001), but for the Yukon River the information had to be extracted from each annual AMR (e.g., Whitmore et al. 1990, Bergstrom et al. 1992, Bergstrom et al. 1997, and Bergstrom et al. 2001).

We used weekly commercial catch data only for the purpose of estimating a consistent catch per unit of effort, CPUE (see below). Weekly catch data was available for only some of the commercial fishing districts. We combined weekly catch from Districts W-1 and W-2 for the Kuskokwim (Figure 1.1), and Districts Y-1, Y-2 and Y-3 for the Yukon (Figure 1.2), both available since 1975. These districts comprised the majority of the commercial catch for their respective drainages and consistent gear types were used within these districts (in contrast, Yukon districts Y-4, Y-5 and Y-6, while available, lumped the catch from set gillnets with that from fish wheels).

1.3.1.4 Commercial Fishery Effort

Commercial fishing effort was estimated as the number of permits multiplied by the hours open for each week (Burkey et al. 2001, Bergstrom et al. 2001). This approach is believed to provide a reasonable representation of the commercial fishery effort on the fishing grounds; however, it is confounded to some degree by variability in the duration of commercial fishing periods. For example, on the Kuskokwim River, the duration of individual chum salmon directed commercial fishing periods has ranged from 12 hours to 1.5 hours.

1.3.1.5 Test-Fish CPUE

Test fisheries are a commonly used inseason management tool where systematic daily net sets are performed to assess run strength and timing throughout the fishing season (Burkey et al. 2001). The Kuskokwim River drift gillnet test fishery is located near Bethel at river mile 80, approximately the mid-point of District W-1 (Figure 1.1). Methodologies have changed relatively little since the onset of this project in 1984 (Molyneaux 1998). Historical CPUE for this project has been recorded each day from early June to late August (Table 1.1). We averaged this daily CPUE data over each week for consistency with the commercial catch and effort data.

The Yukon set gillnet test fishing projects are located at the South, Middle and North Mouths of the Yukon River delta (Figure 1.2). Data from these three test fisheries are pooled together into one dataset termed Big Eddy – Middle Mouth which contains daily CPUE records from early June through July since 1988 (Table 1.1). Again, we averaged the daily CPUE data over the week for consistency with the commercial catch and effort data.

1.3.1.6 Sonar Counts

Whole river sonar counts were available in both regions (Table 1.1). The Kuskokwim River sonar project was a user-configurable system located in the lower river near Bethel, halfway through District W-1 (Figure 1.1). The project operated from 1993 to 1995 (Burkey et al. 1999). The Yukon River sonar project is also a user-configurable system and is located near Pilot Station, approximately half way through district Y-2 (Figure 1.2).

1.3.2 Estimation of an Index of Basin-wide Escapement

Escapement data for the Kuskokwim and Yukon Rivers are only collected in a few tributaries and these represent an unknown fraction of the total escapement for each river. Furthermore, many of the tributary escapement projects were begun in just the past few years. For the Kuskokwim River, the Kogrukluk River weir was the only tributary escapement project with a reliable time series of greater than ten years. Accordingly, we used this single tributary as the escapement index (I_y) for the Kuskokwim system (Figure 1.4a). A time series of data was also available for Aniak River sonar, however these sonar estimates are not apportioned to species and the methodology that is employed has undergone substantial change over the years (Burkey et al. 2002). We therefore decided not to use this data set in this study.

For the Yukon River, twelve tributary escapement projects are available with time series greater than ten years. Nine of the tributary projects have missing data and methodologies used to assess escapement differed among the projects (weir, sonar, tower and aerial surveys). It is not known what fraction of the total escapement these streams constitute. If a common pattern of variability existed among the available tributary projects, then annual PCA scores should be an index (I_y) of the total escapement to the drainage. PCA was applied to extract this pattern (Adkison et al. 1996, Manly 1986). We used PCA on a correlation matrix of the tributary project escapement data to prevent large tributaries from overwhelming small ones.

For our situation, the standard PCA function, shown in equation (1), could not be used to generate all scores due to some missing data. In the following, equation, ω_i are the loadings for an individual tributary (i), $v_{i,y}$ are individual observations (counts) for each tributary (i) for each year (y), μ_i is the mean for each tributary (i) over all years, and σ_i is the standard deviation for each tributary (i) over all years.

(1) $$PC_{1,yr} = \sum_{i=\#rivers} \omega_i * \left(\frac{v_{i,y} - \mu_i}{\sigma_i} \right)$$

To account for missing values, we divided each score generated by equation (1) by the sum of loadings for all tributaries that had counts for that year, and then multiplied the sum of all loadings.

The first principal component (*PC1*) in the Yukon data was dominant, containing 51% of the variability in the escapement data, with loadings on all rivers that were positive and of similar magnitude (Table 1.2). Likewise, correlations between *PC1* and the original escapement data were also positive and generally high (Table 1.2). This supported our hypothesis that a common pattern in escapement exists, and that *PC1* might be proportional to the total escapement to the Yukon River. The second principal component (*PC2*) only explained 13% of the variability and loadings did not exist for every river. The trend in this second component seemed to demonstrate the differences between aerial surveys and the tower, sonar, and weir monitoring. We decided to use only *PC1* as our index of escapement, I_y, (Figure 1.4b) for the analyses described below. This was by far the dominant component and loadings were available for all tributaries allowing a more complete geographic coverage of the drainage basin.

1.3.3 Estimating Abundance and Escapement

Estimation of annual abundance, $\hat{N}_y$, for either the Kuskokwim or Yukon Rivers over all years (y) involved a maximum likelihood statistical framework that simultaneously incorporated four data sets: our escapement index, commercial catch and effort, test-fish CPUE, and whole river sonar. We assumed that I_y was related to annual escapement (E_y) as:

(2) $$E_y = \hat{k}_E I_y + \hat{K}$$

where $\hat{k}_E$ and $\hat{K}$ are scaling constants. This equation simplifies to $E_y = \hat{k}_E I_y$ for the Kuskokwim model, as the Kogrukluk River Weir was assumed to be some constant fraction of the total escapement. E_y is related to total abundance using a simple bookkeeping equation as:

(3) $$\hat{E}_y = \left(\hat{N}_y - C_y - S_y\right)\exp\left[\delta_y\right]$$

where $\hat{N}_y$ is estimated total annual abundance, C_y and S_y are annual recorded commercial and subsistence summer chum catch. $\hat{E}_y$ is assumed to have lognormal random error δ_y with mean zero and standard deviation σ_δ.

We related inseason weekly commercial catch and effort data to abundance for each river in a given time period for a given year ($\hat{N}_{y,d}$) by converting the annual abundance estimates to weekly estimates using a normally distributed run timing curve:

(4) $$\hat{N}_{y,d} = \hat{N}_y \left(\frac{1}{\sqrt{2\pi}\hat{\omega}} \exp\left[\frac{-\left(d-\hat{D}\right)^2}{2\hat{\omega}^2}\right] \Bigg/ \sum_{d=s}^{d=e} \frac{1}{\sqrt{2\pi}\hat{\omega}} \exp\left[\frac{-\left(d-\hat{D}\right)^2}{2\hat{\omega}^2}\right] \right)$$

In this equation, d represents individual weeks, $\hat{D}$ and $\hat{\omega}$ are the run timing mean and standard deviation, respectively, s = start of fishing season and e = end of fishing season. The weekly abundance estimates were then related to catch and effort through a Baranof catch equation (Quinn and Deriso 1999) as:

(5) $$\hat{C}_{y,d} = \hat{N}_{y,d}\left[1-\exp\left(-\hat{q}B_{y,d}\right)\right]\exp[\varepsilon_{y,d}]$$

where, $\hat{C}_{y,d}$ is the estimated catch with lognormal random error $\varepsilon_{y,d}$ having mean zero and standard deviation σ_ε. $B_{y,d}$ is effort (number of permits multiplied by hours fished) in a given week and year, while $\hat{q}$ is another scaling factor termed the catchability coefficient. For both the Kuskokwim and Yukon Rivers, $\hat{q}$ was separated into $\hat{q}_a$ and $\hat{q}_b$ to account for a shift in gear type within the season. Weeks that were primarily fished with unrestricted (8½-inch mesh size) gear were predicted with $\hat{q}_a$, while weeks where openings were primarily restricted (targeting chum salmon with 5½-inch mesh size) were predicted with $\hat{q}_b$ (Burkey et al. 2001, Bergstrom et al. 2001). For the Kuskokwim River this gear shift occurred only in the beginning of the season and up to 1985, after which time commercial fishing was always restricted to the use of gillnets with mesh size of 6 inches or less (Burkey et al. 2001). The shift to a restricted mesh size in the Yukon River typically happened during the middle of the chum salmon run and occurred every year except 1999, when there was very little fishing.

Estimated seasonal test-fish CPUE ($\hat{T}_{y,d}$) over all years was also related to $\hat{N}_{y,d}$ through simple proportions as:

(6) $$\hat{T}_{y,d} = \hat{k}_T \hat{N}_{y,d} \exp[\eta_{y,d}].$$

Here $\hat{k}_T$ is a scaling constant and $\eta_{y,d}$ is lognormal random error with mean of zero and standard deviation σ_η.

The sonar stations for both the Kuskokwim and Yukon Rivers were located approximately halfway through commercial fishing districts, and the Yukon River sonar project was upstream of a major tributary, the Andreafsky River. For simplicity, we choose to extrapolate this data to abundance for both rivers and compared this to our estimates of abundance, $\hat{N}_y$. Therefore, we adjusted the sonar counts to account for possible losses due to fishing or escapement as in the following equations:

(7)
$$\text{Kuskokwim Sonar: } N_y^* = Sonar_{y(Bethel)} + C_{sa} + S_{sa}$$
$$\text{Yukon Sonar: } N_y^* = Sonar_{y(Pilot)} + E_{y(Andreafsky)} + C_{sa} + S_{sa}$$

where, N_y^* is considered the "observed" total abundance for each region. To arrive at this value, we added commercial (C_{sa}) and subsistence (S_{sa}) harvest (Table 1.1) below the sonar sites to the sonar counts for each river. In the Yukon River, tributary escapement counts for the Andreafsky River $E_{y(Andreafsky)}$, East Fork and West Fork combined (Table 1.1), were also added to the sonar counts to determine the approximation of total abundance. $\hat{N}_y$ was then simply the abundance estimate for that year as:

(8)
$$\hat{N}_y = \hat{N}_y \exp\left[\gamma_y\right]$$

where γ_y is lognormal random error on $\hat{N}_y$ having mean zero and standard deviation σ_γ.

Finally, we combined all four datasets (escapement, weekly catch, weekly test-fish CPUE and sonar) to estimate the index of total annual run abundance ($\hat{N}_y$). Residual sum of squares for each dataset were combined using the following likelihood equation:

(9)
$$\ln \mathrm{L} \propto \frac{w_e}{n_e}\sum_y\left(\ln\left(E_y\right)-\ln\left(\hat{E}_y\right)\right)^2 + \frac{w_c}{n_c}\sum_y\sum_d\left[\ln\left(C_{y,d}\right)-\ln\left(\hat{C}_{y,d}\right)\right]^2 +$$
$$\frac{w_t}{n_t}\sum_y\sum_d\left[\ln\left(T_{y,d}\right)-\ln\left(\hat{N}_{y,d}\Big/\hat{k}_T\right)\right]^2 + \frac{w_s}{n_s}\sum_y\left(\ln\left(N_y^*\right)-\ln\left(\hat{N}_y\right)\right)^2$$

The likelihood equation for the commercial catch data was calculated only for weeks 25 to 30 for the Kuskokwim and the designated summer chum season (Bergstrom et al. 2001) for the Yukon (typically weeks 24 to 29) to ensure catches consisted mainly of early run chum salmon. For similar reasons, the likelihood equation for the test-fish CPUE was calculated only for weeks 25 to 30 in the Kuskokwim and weeks 23 to 29 in the Yukon. We divided each likelihood by its number of observations (n_e, n_c, n_t, and n_s) so that each data type would receive equal weight if the weightings (w_e, w_c, w_t, and w_s) were the same.

Weights were chosen based on the quality of data and the correspondence of datasets with each other. Model parameters $\hat{D}, \hat{\omega}, \hat{q}_a, \hat{q}_b, \hat{k}_T, \hat{k}_E, \hat{K}$, and $\hat{N}_y$ for each river were estimated by minimizing this weighted likelihood using a nonlinear search algorithm. Following this, we performed a standard sensitivity analysis on starting values and checked the model output for convergence.

1.3.4 Bootstrapping

Coefficients of variation (CVs) and confidence intervals (CIs) were determined for each parameter through a simple non-parametric bootstrap routine (Efron and Tibshirani 1993, Hilborn and Walters 1992). For each region, we resampled residuals with replacement and added the residual to the logarithm of the predicted values of each element of each dataset to create the bootstrap datasets. Model parameters were recorded for 3,000 bootstrap replicates. We used these replicates to generate CVs and 95% CIs through the percentile method.

1.3.5 Sensitivity to Weighting

Finally, we investigated a range of alternative weighting schemes to determine the sensitivity of the model to changes in our weights. A uniform weight of 1.0 means that each type of data had equal influence on model estimates (equation 9). We explored sequential up-weighting each data type using values of 1.5, 2, 3, 5, and 10 and down-weighting using values of $0.6\overline{6}$, 0.5, $0.3\overline{3}$, 0.2, and 0.1.

We summarized the effect of the different weighting schemes on how well the model was able to match each particular dataset using the unweighted mean squared error (MSE). This provided a relative measure of the goodness of fit. We also recorded the mean percentage difference (MPD) and mean absolute percentage error (MAPE) from our base case for both abundance and escapement estimates as well as the model parameters. This illustrated the overall consequence of a change in weights for the model and pinpointed the estimates most sensitive to our weighting assumptions.

1.3.6 Comparison of PCA and Tributary Only Estimation

A possible drawback to the use of the PCA index in the Yukon abundance and escapement estimation originates from the fact that several of the Yukon tributary escapement estimates used in the PCA are based on aerial surveys. These surveys often contain large amounts of measurement error due to a combination of factors such as off-peak counting, poor survey conditions, and observer bias (Clark 2001). The positive loadings on all rivers in the PCA analysis (Table 1.2) demonstrate that the individual stocks exhibit a strong common pattern of escapement. However, the Andreafsky and

Anvik River counts, which are taken through weir/tower/sonar and represent the majority of Yukon River summer chum salmon, have the lowest correlations with the escapement index. We considered the alternative of simply using the Anvik River sonar counts as the escapement index (similar process as with the Kuskokwim). This tributary has complete data for the time period of study and about half of the Yukon summer chum salmon are believed to spawn in its waters (Clark and Sandone 2001). We compared the Yukon abundance and escapement estimates between the two methodologies (PCA-derived and Anvik only) to demonstrate the effect of our assumptions regarding PCA and the Yukon aerial surveys.

1.4 Results

Initially, we attempted to run this model without the whole river sonar data. However, that attempt resulted in an indeterminate solution because there was not enough information among the three datasets (escapement, commercial catch and effort, and test-fish CPUE) to distinguish between a large run with low efficiency test and commercial fisheries, and a smaller run where fisheries were more efficient. An independent estimate of run abundance was therefore necessary to anchor model estimates. Only a few years of abundance data were required to accomplish this; therefore, the whole river sonar counts were sufficient. Once sonar data was included in the model, estimates of total run abundance for both the Kuskokwim and Yukon Rivers were generated using the maximum likelihood statistical framework.

1.4.1 Weighting of Kuskokwim River Datasets

Kogrukluk River escapement, commercial catch and effort, and whole river sonar data for the Kuskokwim River were considered relatively good information while data from the drift gillnet test-fish CPUE was thought to be biased due to changing catchability (Molyneaux 1998). Water levels, fishing patterns, and river morphology at the test-fish area vary from year to year altering the performance of the test-fishing and managers consider these factors when using this data for inseason assessment (Burkey et al. 2001). The Kogrukluk River project is located in the upper Holitna River sub-basin approximately 300 miles from Bethel (Burkey et al. 2001). It was suspected that the Kogrukluk River project, being distant from the commercial, test, and sonar sites, might not reflect the time series of escapement to the entire Kuskokwim River drainage. There was relatively good agreement between the commercial catch and test-fish CPUE ($r = 0.76$) and correlations of sonar data with these two datasets, although not very informative with only three years of information, showed relatively good agreement with the catch CPUE and extremely good agreement with the test-fish CPUE. However, this agreement with the test-fish CPUE is partly because the test fishery was incorporated into the apportionment of the sonar counts (D. Molyneaux, Alaska Dept. of Fish and Game, personal communication).

The weights chosen were 1, 1, $0.3\overline{3}$, and 1 for the escapement, commercial catch, test fishery CPUE, and sonar data, respectively. The Kogrukluk River project was geographically distant although data was considered good; therefore, we did not up- or down-weight this dataset. Catch and effort were good information but suffered from changes in gear efficiency and regulations over time. Test-fish CPUE was down-weighted for fluctuations in catchability over time, even though the data were in relatively good agreement with sonar and catch. Sonar data were good but consisted of only three data points. These data, therefore, had a relatively large influence already and no extra weighting was deemed necessary.

1.4.2 Weighting of Yukon River Datasets

The Yukon escapement index, I_y, combined information from river projects that covered almost the entire drainage basin (Figure 1.2), stretching from the Salcha River near Fairbanks to Andreafsky River near the delta (approximately 830 miles). These projects contained a strong common signal across the drainage and thus we felt our index provided a fairly good description of the overall escapement trend to the Yukon River basin. Catch data were confounded by numerous gear changes over time but considered relatively good information, while the test-fish CPUE was again thought to be biased due to changes in water level around the test site (T. Lingnau and D. Molyneaux, Alaska Dept. of Fish and Game, personal communication). Catch and test-fish CPUE were in relatively poor agreement ($r = 0.24$). Sonar data was considered relatively good information (C. Pfisterer, Alaska Dept. of Fish and Game, personal communication) and the pattern agreed well with the escapement, test-fish and catch data over the four years available.

Weighting schemes that did not down-weight the catch data relative to the escapement data resulted in poor estimates of the parameter $\hat{k}_E$, and a very poor fit to the escapement data (i.e., a flat line). The final weighting scheme was a balance between up-weighting the escapement and down-weighting the catch. The test-fish CPUE was also down-weighted for changes in catchability over time. We choose 3, $0.3\overline{3}$, $0.3\overline{3}$, and 1 for the escapement, commercial catch, test-fish CPUE, and sonar datasets respectively.

1.4.3 Abundance and Escapement Estimates

Once the weighting scheme was determined, we solved for parameter estimates. The estimated run timing was similar for both drainages; the Yukon River summer chum run was estimated to peak ($\hat{D}$) one week earlier, and the standard deviation about this peak ($\hat{\omega}$) was about 1.7 weeks for both (Table 1.3). In both drainages, the shift to restricted mesh gear seemed to be accompanied by an order of magnitude increase in the fleet's chum salmon harvesting efficiency ($\hat{q}_a$ vs. $\hat{q}_b$ (Table 1.3)).

For the Kuskokwim, the Kogrugluk system was estimated to be $1/13^{\text{th}}$ ($\hat{k}_E$) of the total escapement on average. For the Yukon River, the mean escapement ($\hat{K}$) was estimated to be about 1.6 million fish, and every unit change in the escapement index (Figure 1.4b) was estimated to correspond to 424,000 fish ($\hat{k}_E$).

We produced 25 years of abundance estimates for both areas, from 1976 to 2000 for the Kuskokwim River (Table 1.4, Figure 1.5a) and from 1975 to 1999 for the Yukon River (Table 1.4, Figure 1.5b). Both show decreased abundance in recent years.

Escapement estimates are also low for recent years in both drainages (Table 1.4, Figures 1.6a & 1.6b). We also included the harvest rates implied by these estimates as total harvest (commercial plus subsistence harvest) divided by the abundance estimates (Table 1.4). In general, harvest rates have decreased in the past several years with some fairly high estimated rates on the Kuskokwim River in the late 1980s.

1.4.4 Bootstrapping

For Kuskokwim model parameters, the commercial fleet efficiencies $\hat{q}_a$ and $\hat{q}_b$ had the largest CVs, followed by the parameter that scaled the fluctuations in the escapement index $\hat{k}_E$ (Table 1.3). The smallest CV was on the mean date of the chum run, $\hat{D}$. CVs of the abundance estimates were relatively small, with that for 2000 being the largest followed by that for 1996 (Table 1.4). There was a small amount of skew about the model parameters and abundance estimates as seen in the 95% CIs (Figure 1.7a, Figure 1.5a).

The largest CV for model parameters in the Yukon was for $\hat{k}_E$, followed by that for $\hat{q}_b$ and then $\hat{q}_a$ (Table 1.3). The smallest CV was, again, that for the mean run timing, $\hat{D}$. CVs of the abundance estimates were larger than for the Kuskokwim with that for 1975 as the largest followed by those for 1994 and 1984 (Table 1.4). There was also a small amount of skew present in the model parameters and abundance estimates as with the Kuskokwim (Figure 1.7b, Figure 1.5b).

1.4.5 Sensitivity to Weighting of Datasets

We present seven trials (Trial 1 to 7) from this investigation to demonstrate the consequences of changing weights for both the Kuskokwim and Yukon models (Table 1.5). The preferred weighting scheme is given first with the label BASE followed by the seven trials.

1.4.5.1 Kuskokwim Sensitivity

Estimates produced from the equal weighting scheme (Trial 1) for the Kuskokwim were not very different from those of the preferred weighting (BASE; Table 1.5). Increased weight to the escapement data altered the data fit, yet caused little change to the abundance and escapement estimates (Trial 2). Model fit to the catch data was not affected by the weighting scheme. This is shown specifically in Trial 3; even with a relatively large increase in weight the catch error (MSE_C) did not change substantially.

A high weight on the test-fish data (Trial 4) or catch data (Trial 3) or a low weight on the sonar data (Trial 6) resulted in an increase in abundance and escapement estimates. Increasing the weight on the test-fish data had the additional effect of substantially improving the fit to those data while degrading the fit to the escapement index. In general, escapement estimates were more sensitive to alternative weighting schemes than abundance estimates.

1.4.5.2 Yukon Sensitivity

For the Yukon, equal weighting of all data types (Table 1.5) resulted in an estimate of zero for the parameter $\hat{k}_E$, with the result that the escapement estimates did not vary from year to year (Trial 1). Some combination of up-weighting the escapement and/or down-weighting the catch data was necessary to achieve non-constant escapement estimates. In this case, escapement estimates were slightly more sensitive to alternative weighting schemes than abundance estimates. In all weighting schemes the catch data, and to a lesser extent the test-fish data, were poorly fit by the model.

1.4.6 Method Comparison of PCA and Tributary Only Estimation

Anvik only abundance estimates deviated from PCA-derived estimates by an average of 17% (absolute difference), and were on average 8% greater in magnitude. Also, Anvik only escapement estimates differed from PCA-derived estimates by an average of 26% (absolute difference), and were on average 12% greater in magnitude. The CVs across the time-series of the PCA-derived estimates were 29% and 25% for abundance and escapement respectively, while the CVs across time of the Anvik only estimates were 40% and 48% for abundance and escapement respectively. There was also relatively high agreement between the two time series of both the abundance and escapement estimates (r = 0.83 and 0.66, respectively, Figures 1.8a & 1.8b).

1.5 Discussion

Management decisions for chum salmon in the Kuskokwim and Yukon Rivers are largely based on qualitative assessments of chum salmon abundance and escapement. Managers consider recent trends in escapement counts, commercial harvests and test-fish CPUE when determining harvest strategies. It is clear that these data are valuable, and that managers would benefit from a rigorous, quantitative analysis summarizing all available information. We developed estimates of total abundance and escapement for the Kuskokwim and Yukon River drainages using diverse escapement indices, annual and weekly commercial catch and effort, subsistence harvests, test-fish CPUE and whole river sonar enumeration. Additionally, we determined that PCA effectively summarizes tributary escapement data for large rivers such as the Yukon and that an independent assessment of abundance was necessary for our model.

Recently, Clark (2001) and Clark and Sandone (2001) developed tributary based abundance estimates for the Andreafsky and Anvik Rivers. Their purpose was to develop a stock-recruitment relationship for the individual tributaries to aid in setting appropriate biological escapement goals for summer chum salmon (Clark and Sandone 2001). The estimates relied on several assumptions to produce a complete time series of escapement and abundance for both rivers. Comparisons of our estimates with those of Clark and Sandone are difficult as we developed a more comprehensive statistical framework and produced whole drainage abundance and escapement estimates. However, the Anvik escapement estimates are considered to be approximately 50% of the counts at Pilot Station (Clark and Sandone 2001). We were able to generate a simplified comparison with the Anvik estimates by doubling the Clark and Sandone (2001) estimates. On average, the Clark and Sandone (2001) estimates differed from the PCA-derived estimates by 21% (absolute difference) and were on average 18% greater in magnitude. The pattern over time was relatively consistent (Figure 1.9, r = 0.80). The PCA-derived abundance estimates were less variable than the Clark and Sandone (2001) estimates with CVs of 29% and 40% respectively. While this comparison is very rough, it does show a general coherence between the two sets of estimates which is encouraging considering the estimates were generated through different methodologies.

Historical data from ADFG tributary escapement projects along the Kuskokwim and Yukon Rivers produced an incomplete estimate of the total escapement to these drainages. PCA was useful to extract a common pattern from data in the Yukon River collected through very different methodologies (aerial, tower, weir, and sonar). Several studies have utilized this aspect of PCA to develop indices for further analysis (e.g., Hare et al. 1999, Pyper and Peterman 1999). The Yukon PCA resulted in loadings that were all positive and relatively equal in magnitude. This is an important property as it identifies a trend that extends over the entire basin and, therefore, suggests the influence of a large-scale forcing agent on summer chum salmon survival. Alternatively, if the loadings on individual tributaries were of different signs this would suggest that the trend was not consistent across the basin. A more appropriate method would then be to simply use the most representative tributary data set as the escapement index, similar to the methods described for the Kuskokwim River. However, we can surmise that because this pattern explained a large amount of variation in the escapement data over a vast geographic area, a major source of mortality occurs when the fish are in a common environment (e.g., near-shore marine, open-ocean). This concept may apply to the Kuskokwim River as well, although limited long-term time series of escapement from tributary projects precludes identification of a common trend through PCA. However, some of the potential "common" variability was still represented in the Kogrukluk River counts. We suggest the monitoring of tributary escapement projects be maintained to generate a longer, more substantial escapement database, particularly for the Kuskokwim River.

The Yukon PCA escapement index largely draws on the information in the aerial tributaries as this type of survey comprises the majority of escapement monitoring in the Yukon. This produces a caveat, in that the aerial data is believed to contain a large amount of measurement error (Clark 2001), and the two largest summer chum salmon producing rivers with weir/tower/sonar counts have the lower correlations with the PCA index. There are, therefore, two alternatives to interpretation of the escapement index. Either the aerial surveys are on the whole poor estimates of escapement and the trend represents aerial survey sampling problems common to all drainages, or the aerial surveys in combination adequately describe escapement trends across the basin and the larger rivers behave slightly differently from the smaller ones. These two alternatives require different modeling approaches. We considered an alternative methodology of simply using the Anvik River sonar counts as the escapement index and presented the difference in the abundance and escapement estimates derived from the two methods. The two indices were different with the Anvik-only estimates being larger in magnitude and more variable than the PCA-derived estimates. However the temporal patterns did agree relatively well. Furthermore, we did compare our Anvik only abundance estimates with the doubled Anvik estimates presented in Clark and Sandone (2001). Again, the two time series agree very well in temporal pattern (Figure 1.9, r = 0.99), although the estimates of Clark and Sandone 2001 were on average 12% greater than the Anvik only estimates. These comparisons indicate a general coherence in temporal pattern but some difference in magnitude between PCA-derived and Anvik-only estimates. Given this, one might consider the simpler Anvik-only approach to be more reasonable for management purposes. However, the PCA index explained a considerable amount of variability in the first principal component (*PC1*) and there was consistency in the loadings on each tributary. Anvik-only estimates would only represent a pattern over time from that single tributary. Furthermore, the separation by sampling method seemed to be well characterized in the second principal component (*PC2*) where minimal additional variability was explained. Our escapement index only used *PC1*, so variability due to the differences in sampling methodology was not included in our index. We, therefore, recommend using PCA to derive the escapement index in this methodology under similar conditions such as that found on the Yukon River.

A fundamental assumption of our PCA approach is that a drainage-wide index adequately describes the variability in total escapement and hence run strength among all stocks. Escapement monitoring occurs on only a few tributaries along the Kuskokwim and Yukon Rivers; therefore, the variability from individual stocks that are not surveyed is unknown. When we use PCA to extract a common signal from the available tributaries, we state that survival can be determined at the region wide scale. This approach will blur any underlying true variation from individual stock units. However, Pyper et al. (2002) demonstrated strong covariation of chum salmon survival at the local and regional scales (up to 1000 km) over 40 wild and 27 hatchery stocks from 15 geographic locations along the Northeast Pacific. This provides strong support for our methodology that assumes run strength is highly correlated within a drainage system. Additionally, the properties of PC1 (all positive and relatively equal weighting) support this concept. We feel that the PCA-derived abundance and escapement estimates are useful for future testing of mechanisms underlying physical forcing using traditional stock-recruitment methods (Adkison et al. 1996; Peterman et al. 1998).

The estimates generated in our approach required the inclusion of whole river sonar enumeration. Without such data, the abundance estimates and certain scaling parameters of the model were confounded. This issue was particularly important in the Yukon PCA-derived abundance model where two escapement scaling parameters were estimated. Also, because the rest of the data in the model were consistent with a variety of abundance levels, any bias in the sonar enumeration would be transferred to our abundance estimates. Therefore, the sonar counts needed to be a good approximation of abundance due to this dependence of the model on sonar information. One potential problem with sonar counts is species apportionment. The Kuskokwim mainstem sonar was problematic due to differences in the distribution of the various salmon species throughout the water column. Initially, species apportionment for the Kuskokwim sonar counts was based solely on the Bethel Test Fishery. This information was later augmented by a series of drift sets using other mesh sizes. Eventually set nets were added to help understand the horizontal species distribution (Burkey et al. 1999). Species apportionment was clearly difficult in this case and indices based on these methods may contain biases. This could contribute to the error in our abundance and escapement estimates. However, given the paucity of information on the Kuskokwim, the whole river sonar program is the best we have available (D. Molyneaux, Alaska Dept. of Fish and Game, personal communication). Our model would certainly benefit from continued and improved independent estimates of total escapement or abundance such as mainstem sonar and mark-recapture programs.

It is important to examine several other assumptions that were required for our approach. In the commercial fishery, the two catchability coefficients only accounted for recorded changes in mesh size over time. There may be other aspects of the commercial fishery that varied from year to year that were not considered in our catch equation. Also, the measure of effort we used was permits multiplied by the hours fished. This measure may not adequately capture the effect of systematic changes in the duration of fishing periods over time, or of other regulatory changes. Other potential difficulties were the scaling parameters for the test-fish CPUE and escapement data. In the equations, these were modeled as fixed measures of proportionality. For the test fishery, the value may change from year to year, even if the survey methods have not been substantially altered, due to changes in the topography of the river or changes in the behavior of the fish.

The bootstrap CVs of model parameters reflected some of these concerns about the assumptions. The largest CV in the Kuskokwim River surrounded the catchability coefficient, while in the Yukon River it was the CV about the escapement scalar. There were also some abundance estimates with large CVs, such as 2000 and 1975 for the Kuskokwim and Yukon respectively. However, the CVs about the model parameters and abundance estimates demonstrate the error on each estimate due to the modeling process and not the potential measurement error about the empirical data used in the model. The weighting scheme does provide for some regulation of the relative influence from each dataset on the estimates as reflects our confidence in the data. There was some sensitivity in the magnitude of the estimates to the weighting on individual datasets and we found the weighting on the catch data to be particularly influential. As stated previously our estimates were smaller in magnitude than previous studies have suggested (Clark and Sandone 2001). With this in mind, managers may consider the harvest rates implied by our estimates as unrealistically high, particularly for the Kuskokwim River where the reliability of sonar data was not well known (D. Molyneaux, Alaska Dept. of Fish and Game, personal communication). We recommend that managers validate the assumptions of a particular weighting scheme for estimation of abundance and escapement by inspecting potential datasets for large sources of measurement error. We further suggest including the estimated uncertainty on model parameters and estimates as shown by the bootstrap CVs when developing escapement goals from these estimates.

Our model begins the process of quantitative stock assessment and forecasting in these rivers. The next step would be to combine the abundance estimates with information on environmental influence in a stock-recruitment model. The ability to combine multiple data types in a statistical framework to develop these estimates demonstrates the utility of this model for assessing population dynamics in data-limited systems. A similar approach could certainly be applied to other regions and different semelparous species. Investigators could tailor the model to the specific region of interest and the available information. An example where this model would be appropriate is for the Southeast Alaska pink salmon fishery where estimates of total abundance and escapement are limited by the coverage and conversion factors involved in their aerial escapement surveys (Zadina et al. 2003). In conclusion, this modeling application combines the features of PCA and maximum likelihood to surmount the limitations of qualitative assessments in data-limited regions. We believe that future management decisions could benefit from these results provided that managers consider the assumptions inherent in the model.

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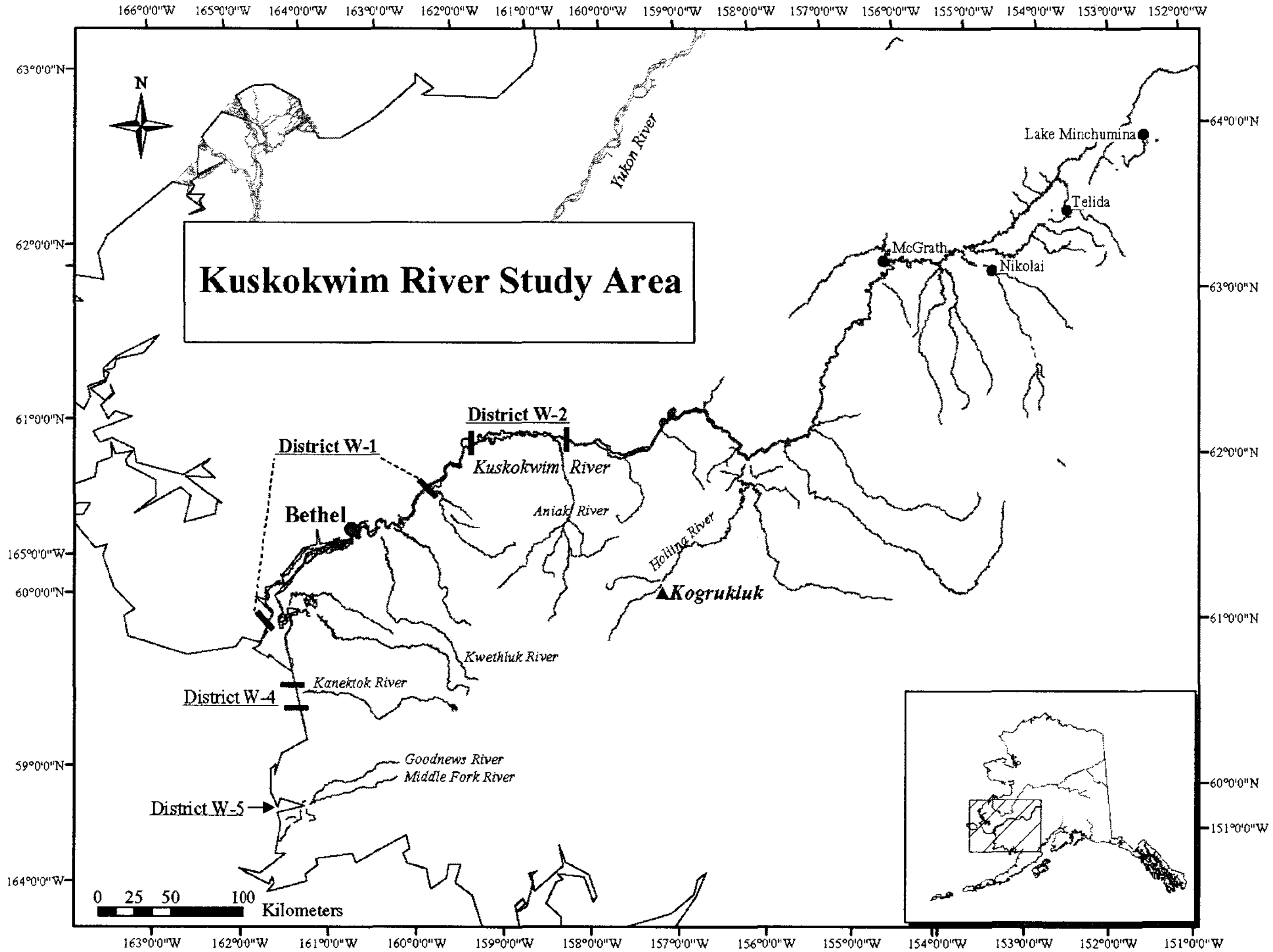


Figure 1.1. Kuskokwim River study area.

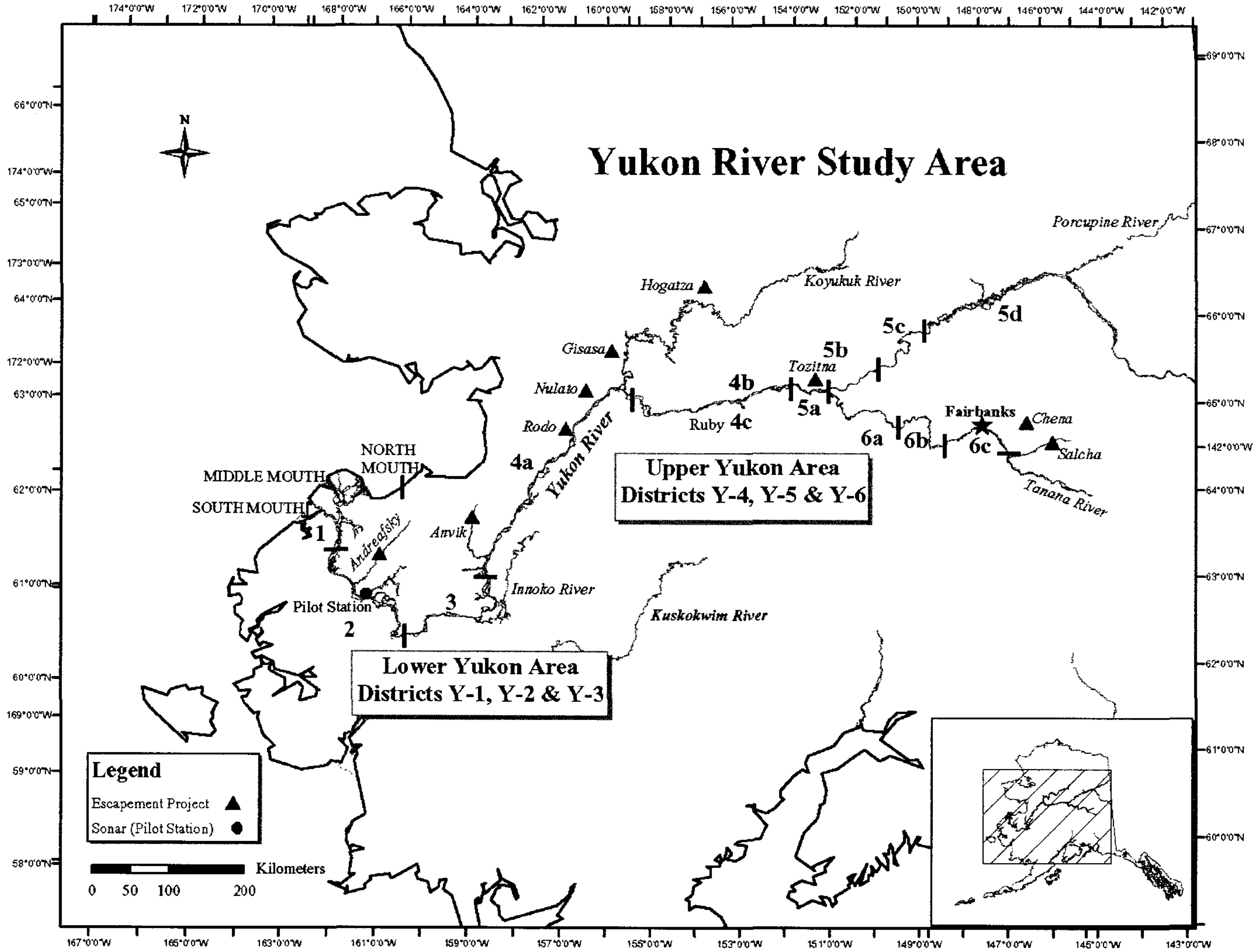
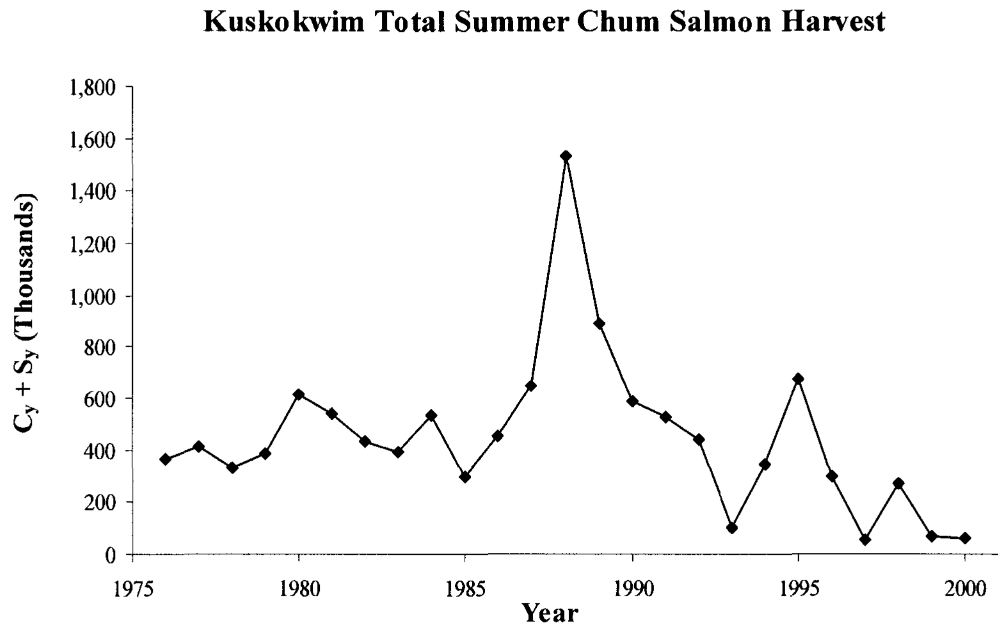


Figure 1.2. Yukon River study area.

a)



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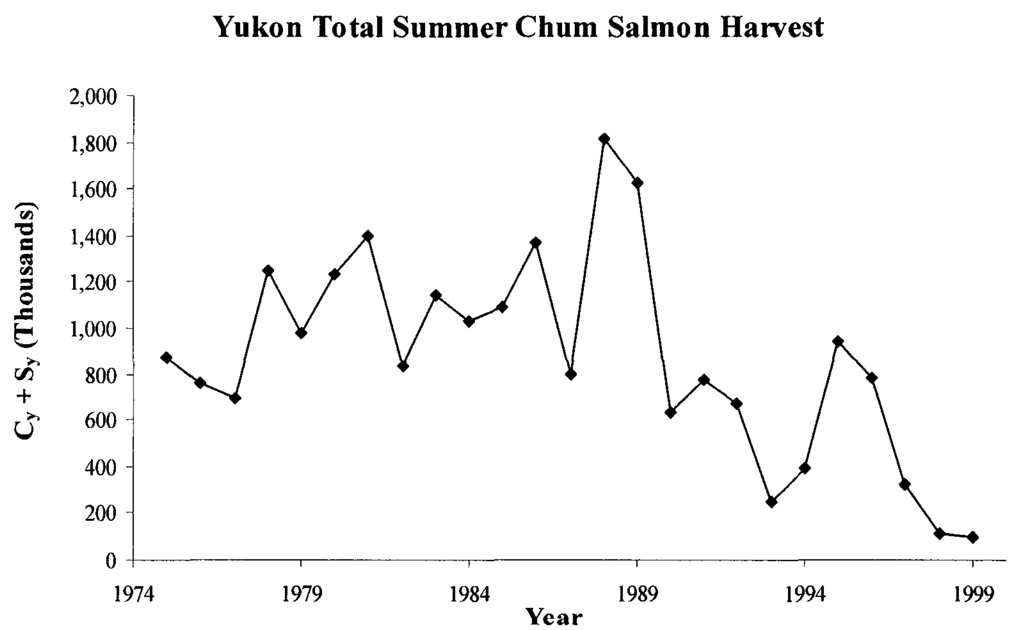
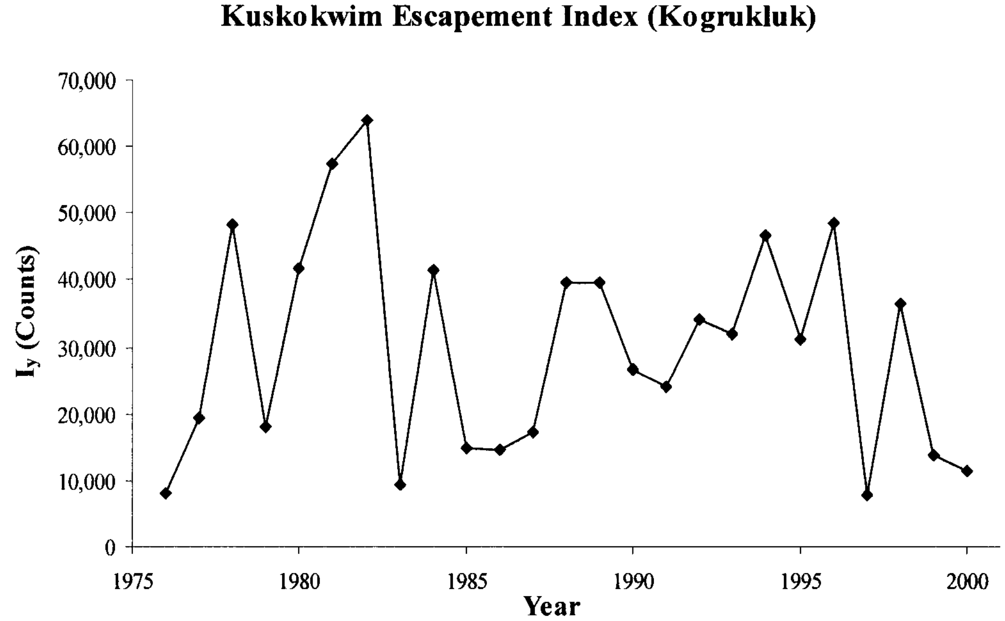


Figure 1.3. Annual commercial catch, C_y, plus annual subsistence harvest, S_y, of summer chum salmon for (a) Kuskokwim River over the years 1976 to 2000 and (b) Yukon River over the years 1975 to 1999.

a)



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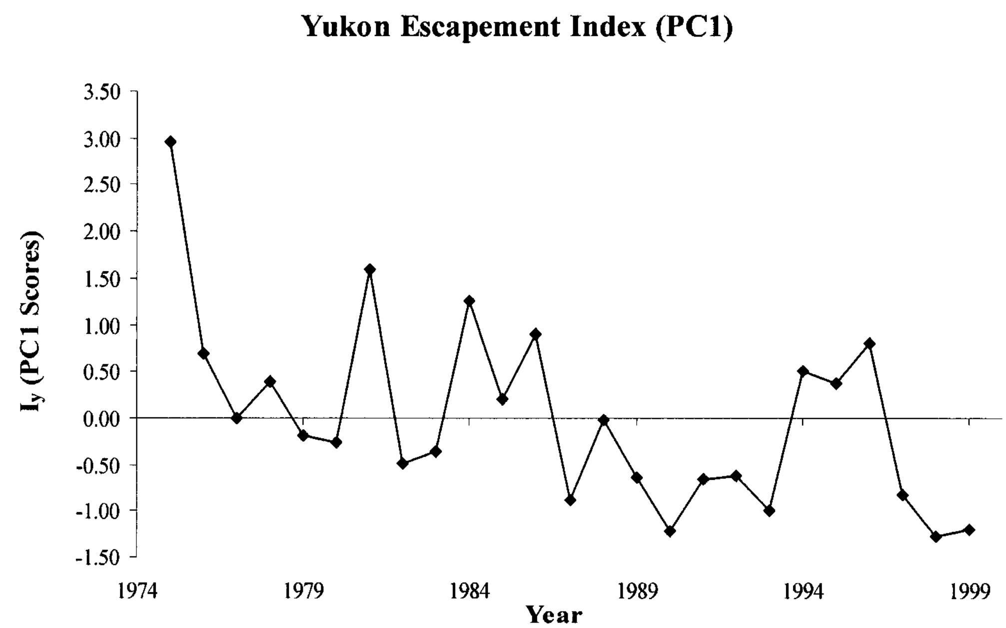
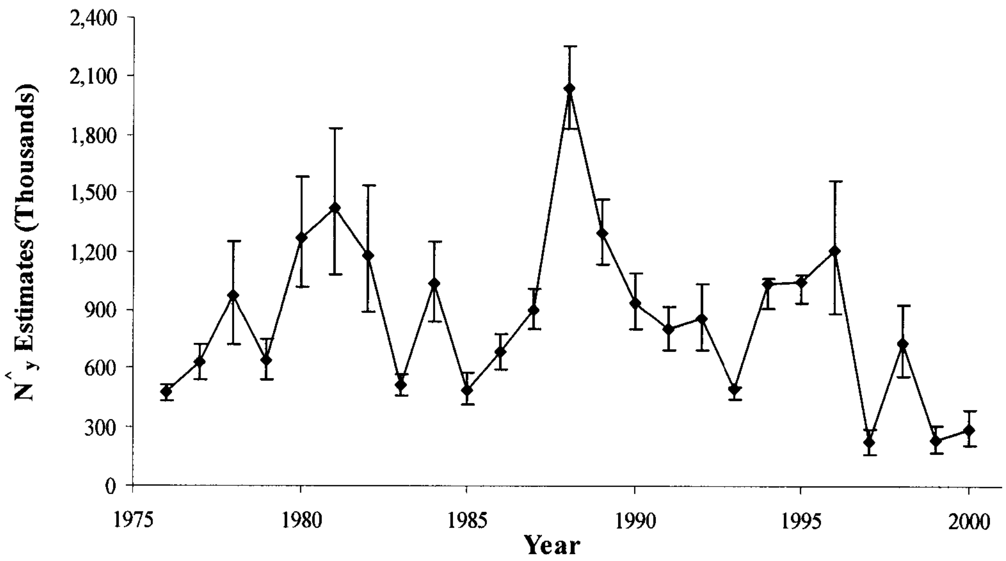


Figure 1.4. (a) Escapement index, I_y, for the Kuskokwim River. These are the Kogrukluk River weir counts from 1976 to 2000. (b) Escapement index, I_y, for the Yukon River. This is the time series of scores for principal component one (PC1) from Yukon principal component analysis (PCA) over the years 1975 to 1999.

a)

Kuskokwim Abundance Estimates (Percentile Method)



b)

Yukon Abundance Estimates (Percentile Method)

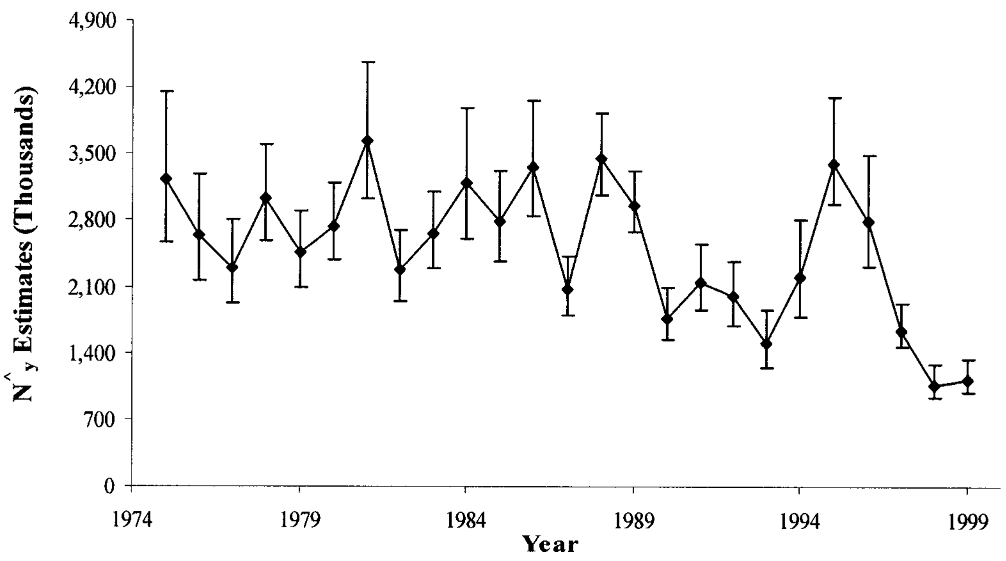
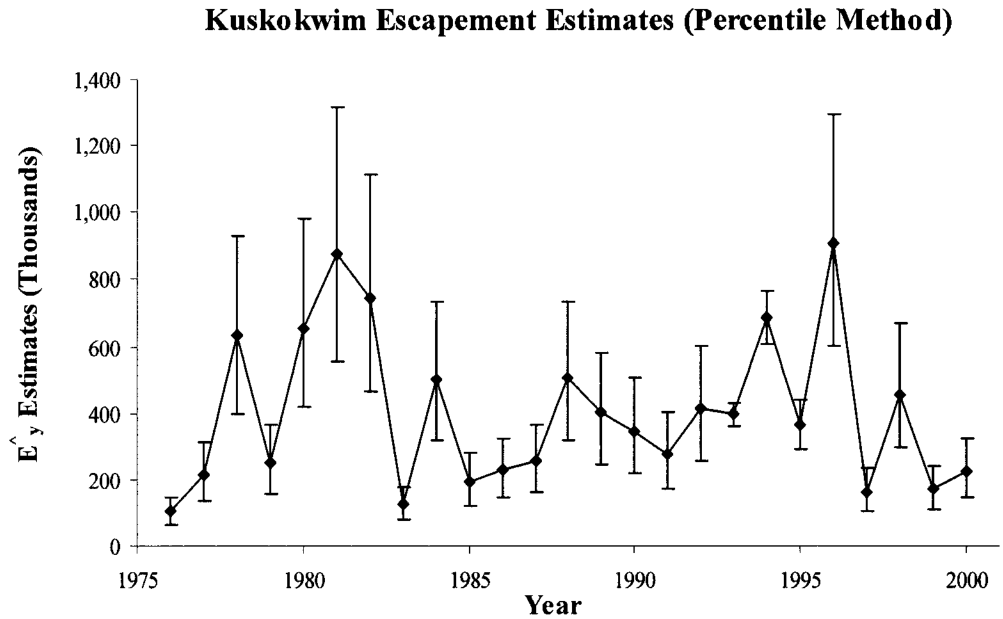


Figure 1.5. Abundance estimates, $\hat{N}_y$, with 95% bootstrap confidence intervals based on the percentile method of the bootstrap estimates for (a) Kuskokwim River over the years 1976 to 2000 and (b) Yukon River over the years 1975 to 1999.

a)



b)

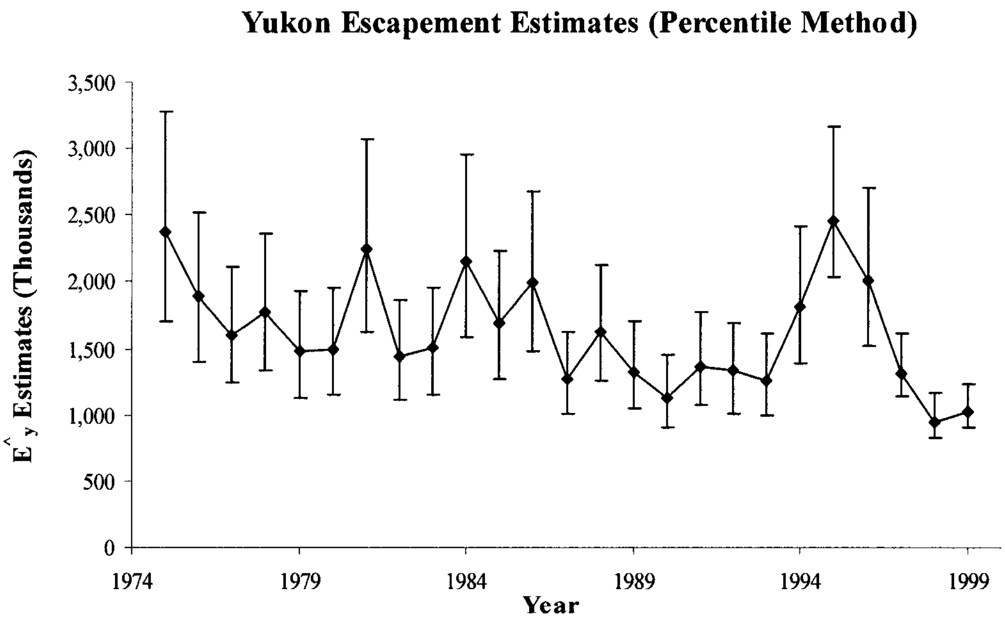


Figure 1.6. Escapement estimates, $\hat{E}_y$, with 95% bootstrap confidence intervals based on the percentile method of the bootstrap estimates for (a) Kuskokwim River over the years 1976 to 2000 and (b) Yukon River over the years 1975 to 1999.

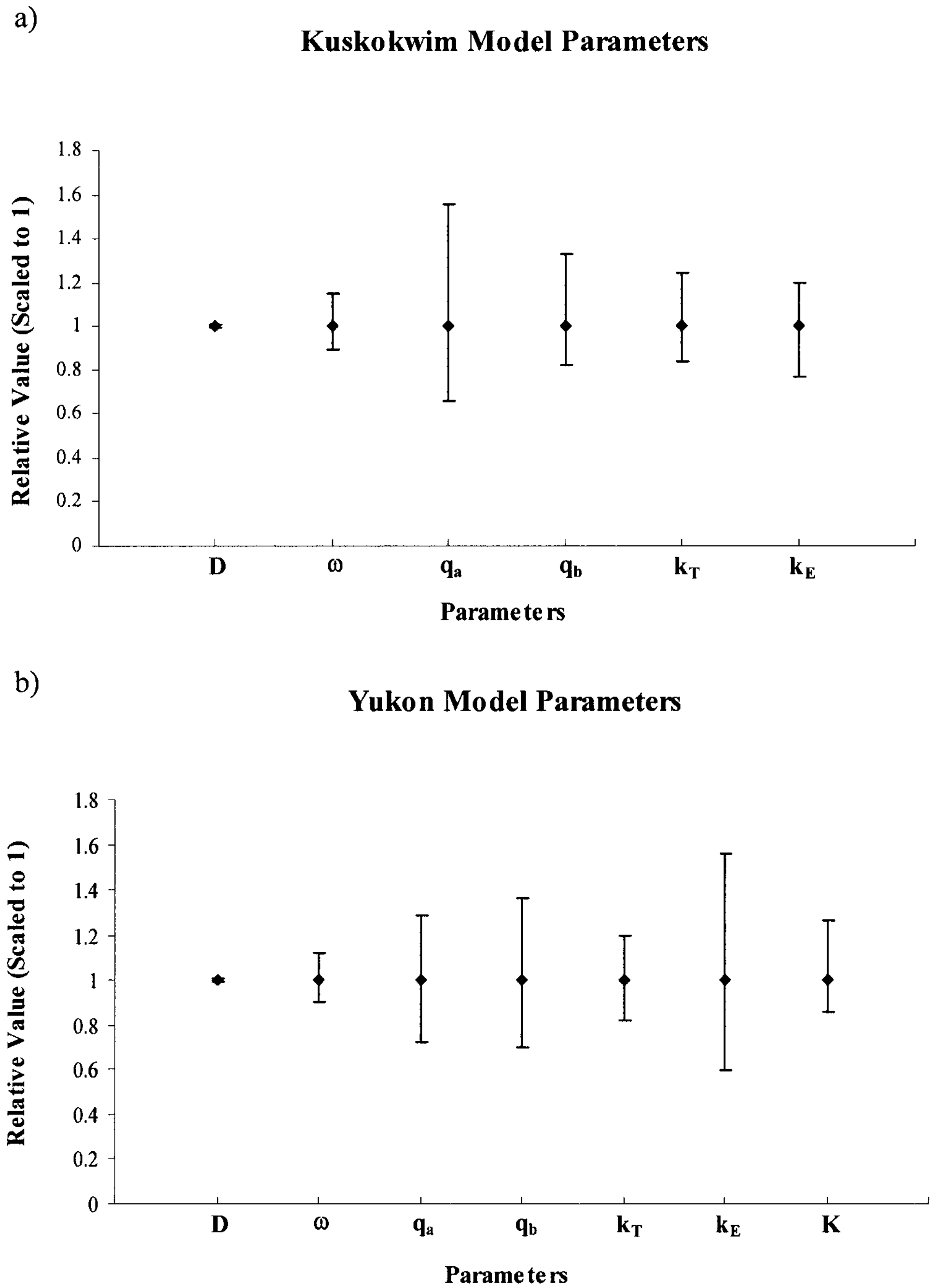


Figure 1.7. Model parameter comparisons of (a) $\hat{D}$, $\hat{\omega}$, $\hat{q}_a$, $\hat{q}_b$, $\hat{k}_T$, and $\hat{k}_E$ for the Kuskokwim River model and (b) $\hat{D}$, $\hat{\omega}$, $\hat{q}_a$, $\hat{q}_b$, $\hat{k}_T$, $\hat{k}_E$, and $\hat{K}$ for the Yukon River model. In both cases, 95% bootstrap confidence intervals are developed by the percentile method on the bootstrap estimates. The intervals are divided by the estimate value to allow for visual comparison across distribution of error for each parameter. Estimates are just the relative value of one.

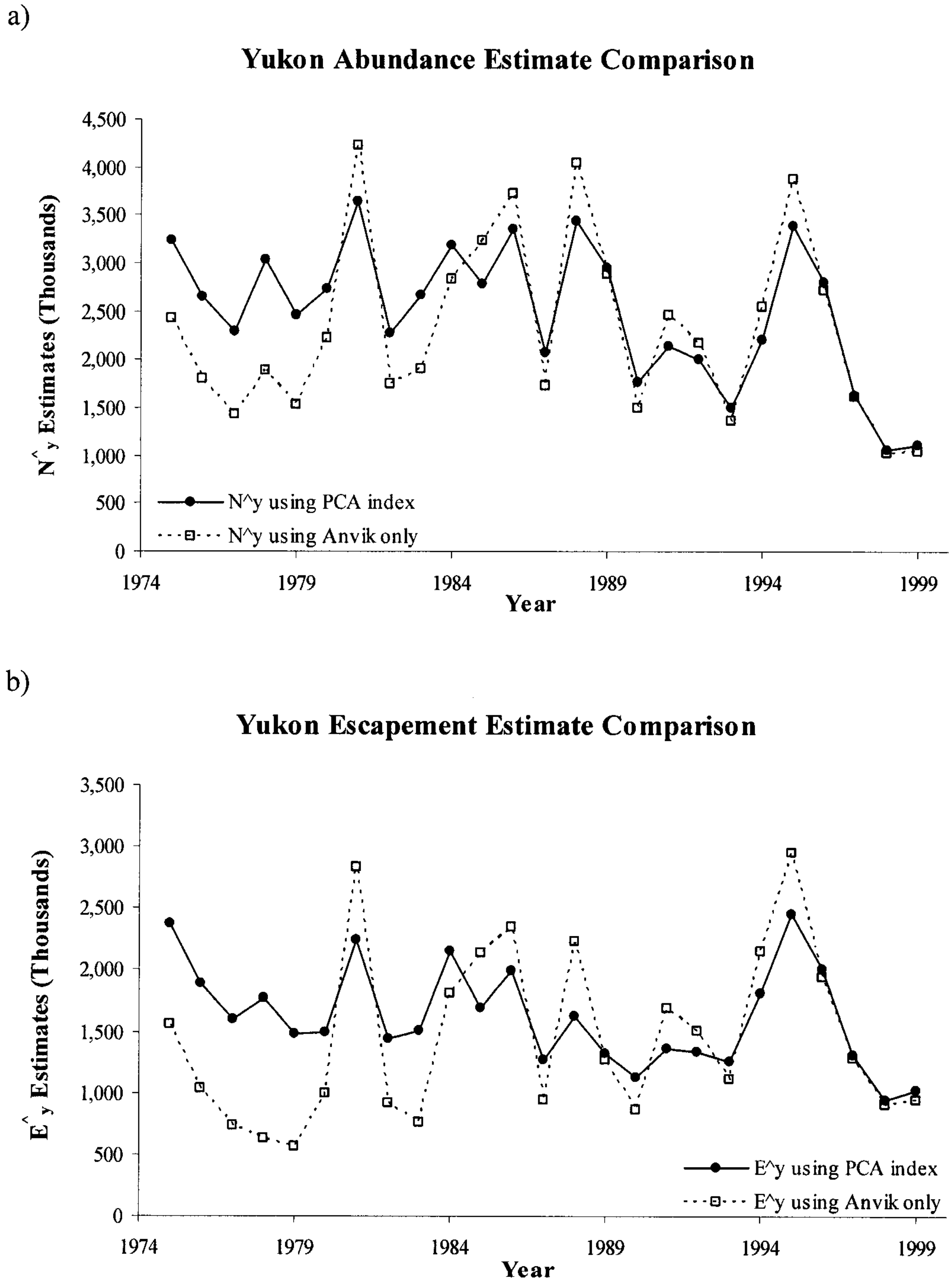


Figure 1.8. Comparison between PCA-derived (solid line with filled circles) and Anvik only (dashed line with open squares) estimation over the years 1975 to 1999 for (a) abundance estimates, $\hat{N}_y$, and (b) escapement estimates, $\hat{E}_y$.

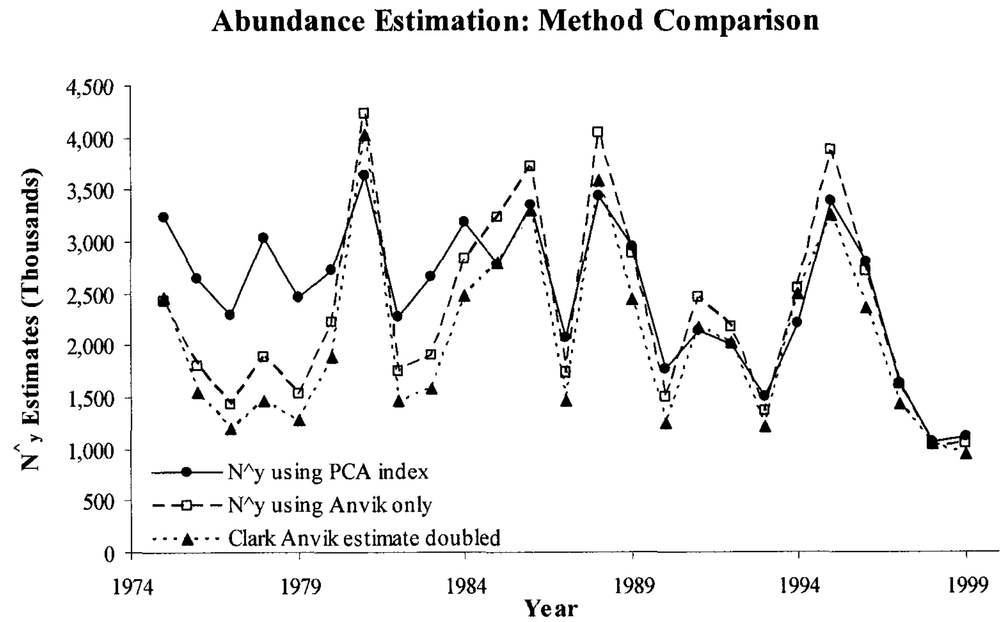


Figure 1.9. Comparison of abundance estimates over differing methodologies. Displayed are the PCA-derived (solid line with filled circles) and Anvik only (large dash line with open squares) estimates along with the doubled Clark and Sandone (2001) Anvik estimates (small dash line with solid triangles) over the years 1975 to 1999.

Table 1.1: Summary of data used to generate abundance and escapement estimates of summer chum salmon in the Kuskokwim and Yukon Rivers. Years used in the analysis and data sources are separated by river.

Data	Years used in data analysis		Data Source[a]	
	Kuskokwim	Yukon	Kuskokwim	Yukon
Escapement (Spawner Counts)	1976-2000	1975-1999	1	2, 3
Annual Subsistence Harvest	1976-2000 1985-2000	1977-1999	1	2
Annual Commercial Harvest	1976-2000	1975-1999	1	2
Weekly Commercial Harvest	1976-2000	1975-1999	1	4
Weekly Commercial Effort	1976-2000	1975-1999	1	4
Weekly Test-Fish CPUE	1984-2000	1988-1999	5	6
Mainstem Sonar	1993-1995	1995, 1997-1999	5	7
Commercial Harvest by statistical area	1993-1995	1995, 1997-1999	5	2
Subsistence Harvest by Village	1993-1995	1995, 1997-1999	5	2

[a]Data Sources:

1. Burkey et al. (2001)
2. Bergstrom et al. (2001)
3. Clark (2001)
4. 25 sources: e.g., Whitmore et al. (1990), Bergstrom et al. (1992), Bergstrom et al. (1997), and Bergstrom et al. (2001)
5. Doug Molyneaux, Kuskokwim Area Research Biologist, Alaska Dept. of Fish and Game, Anchorage, Alaska, personal communication
6. Tom Vania, Yukon Area Management Biologist, Alaska Dept. of Fish and Game, Anchorage, Alaska, personal communication
7. Carl Pfisterer, AYK Regional Sonar Biologist, Alaska Dept. of Fish and Game, Fairbanks, Alaska, personal communication

Table 1.2: Tributary projects and survey type for Yukon Principal Components Analysis (PCA). Correlations represent the r-value for each tributary escapement project original counts to Yukon escapement index, I_y. Loadings are the eigenvalues for each tributary escapement project. Notice correlations and loadings are positive and loadings are relatively similar in magnitude.

Tributary Project	Escapement Data	Loadings	Correlation
Andreafsky River	East Fork Aerial	0.36	0.88
	East Fork Counts	0.19	0.52
	West Fork Aerial	0.35	0.87
Anvik River	Tower & Sonar Counts	0.18	0.56
Chena River	Aerial	0.26	0.70
Gisasa River	Aerial	0.35	0.89
Hogatza River	Aerial	0.19	0.45
Nulato River	North Fork Aerial	0.36	0.89
	South Fork Aerial	0.33	0.82
Rodo River	Aerial	0.26	0.63
Salcha River	Aerial	0.29	0.78
Tozitna River	Aerial	0.26	0.65

Table 1.3. Estimates for all model parameters in both regions. D and ω are the run timing mean and standard deviation, respectively, q_a and q_b are the catchability coefficients for unrestricted and restricted fishing periods, respectively, k_t is the test-fish CPUE scaling constant, and k_e and K are the escapement index scaling constants. Parameters k_E and K for the Yukon are rounded to the thousands place. Includes 95% bootstrap lower and upper bounds and coefficient of variation (CV).

Model Parameters	Estimate	Lower Bound	Upper Bound	CV (%)
Kuskokwim Model				
D	27.02	26.77	27.22	2.37
ω	1.71	1.53	1.96	7.32
q_a	1.18E-05	7.78E-06	1.84E-05	23.21
q_b	1.64E-04	1.34E-04	2.19E-04	14.32
k_T	4.48E-04	3.75E-04	5.59E-04	10.53
k_E	13.58	10.42	16.21	11.28
Yukon Model				
D	25.90	25.67	26.11	0.44
ω	1.77	1.60	1.99	5.73
q_a	4.40E-06	3.17E-06	5.67E-06	14.54
q_b	2.54E-05	1.78E-05	3.47E-05	17.18
k_T	7.87E-06	6.47E-06	9.41E-06	9.64
k_E	424,000	253,000	662,000	25.35
K	1,619,000	1,387,000	2,042,000	10.26

Table 1.4. Mean abundance ($\hat{N}_y$) and escapement ($\hat{E}_y$) estimates for Kuskokwim and Yukon areas. Includes 95% bootstrap lower and upper bound (LB and UB, respectively) and coefficient of variation (CV) for each estimate.

	Abundance				Escapement				Harvest
Kuskokwim	$\hat{N}_y$	LB	UB	CV (%)	$\hat{E}_y$	LB	UB	CV (%)	Rate (%)
1976	472,000	430,000	515,000	4.52	107,000	64,000	149,000	20.02	77.43
1977	627,000	542,000	721,000	7.16	216,000	131,000	310,000	20.76	65.52
1978	968,000	718,000	1,247,00	14.25	636,000	386,000	916,000	21.68	34.26
1979	637,000	538,000	746,000	8.38	250,000	151,000	359,000	21.35	60.74
1980	1,267,000	1,017,000	1,578,00	11.23	654,000	404,000	965,000	21.76	48.38
1981	1,416,000	1,075,000	1,836,00	13.42	876,000	535,000	1,296,00	21.69	38.13
1982	1,178,000	894,000	1,534,00	13.76	746,000	461,000	1,102,00	21.74	36.70
1983	514,000	462,000	564,000	5.12	126,000	75,000	176,000	20.88	75.48
1984	1,031,000	838,000	1,252,00	10.26	501,000	308,000	721,000	21.12	51.42
1985	488,000	410,000	571,000	8.25	194,000	116,000	277,000	20.76	60.26
1986	681,000	593,000	772,000	6.92	230,000	142,000	321,000	20.50	66.25
1987	901,000	798,000	1,005,00	5.83	256,000	153,000	360,000	20.53	71.62
1988	2,045,000	1,836,000	2,255,00	5.75	511,000	302,000	721,000	21.92	75.00
1989	1,290,000	1,129,000	1,465,00	6.55	401,000	240,000	576,000	21.07	68.89
1990	936,000	798,000	1,086,00	7.88	348,000	210,000	498,000	21.18	62.81
1991	801,000	692,000	920,000	7.16	276,000	167,000	395,000	20.79	65.56
1992	853,000	690,000	1,038,00	10.36	412,000	249,000	597,000	21.45	51.71
1993	499,000	438,000	505,000	3.70	396,000	335,000	403,000	4.66	20.60
1994	1,030,000	905,000	1,059,00	3.88	687,000	562,000	716,000	5.82	33.31
1995	1,043,000	931,000	1,077,00	3.61	369,000	257,000	404,000	10.19	64.62
1996	1,205,000	877,000	1,567,00	14.91	908,000	581,000	1,270,00	19.78	24.64
1997	221,000	160,000	287,000	14.79	164,000	103,000	230,000	19.94	25.84
1998	730,000	556,000	927,000	12.82	459,000	284,000	655,000	20.41	37.18
1999	237,000	171,000	305,000	14.60	171,000	104,000	238,000	20.30	28.07
2000	288,000	203,000	385,000	15.84	224,000	140,000	322,000	20.31	21.99

Table 1.4. Continued

	Abundance				Escapement				Harvest
Yukon	$\hat{N}_y$	LB	UB	CV (%)	$\hat{E}_y$	LB	UB	CV (%)	Rate (%)
1975	3,239,000	2,574,000	4,151,000	11.94	2,368,000	1,703,000	3,280,000	16.33	26.89
1976	2,643,000	2,162,000	3,285,000	10.38	1,882,000	1,400,000	2,523,000	14.58	28.81
1977	2,296,000	1,934,000	2,808,000	9.15	1,601,000	1,239,000	2,113,000	13.11	30.25
1978	3,025,000	2,590,000	3,604,000	8.06	1,776,000	1,341,000	2,355,000	13.73	41.30
1979	2,454,000	2,101,000	2,901,000	7.63	1,479,000	1,125,000	1,926,000	12.66	39.75
1980	2,729,000	2,393,000	3,188,000	6.96	1,494,000	1,157,000	1,953,000	12.72	45.27
1981	3,639,000	3,022,000	4,461,000	9.83	2,242,000	1,625,000	3,063,000	15.95	38.40
1982	2,273,000	1,944,000	2,699,000	7.83	1,438,000	1,110,000	1,865,000	12.38	36.72
1983	2,656,000	2,300,000	3,093,000	7.20	1,510,000	1,154,000	1,948,000	12.66	43.13
1984	3,186,000	2,613,000	3,979,000	10.57	2,153,000	1,580,000	2,947,000	15.64	32.41
1985	2,789,000	2,369,000	3,315,000	8.18	1,697,000	1,278,000	2,223,000	13.44	39.15
1986	3,357,000	2,847,000	4,050,000	8.77	1,986,000	1,476,000	2,678,000	14.82	40.84
1987	2,070,000	1,801,000	2,419,000	7.19	1,272,000	1,004,000	1,622,000	11.69	38.53
1988	3,445,000	3,071,000	3,935,000	6.19	1,629,000	1,255,000	2,119,000	13.08	52.70
1989	2,948,000	2,674,000	3,325,000	5.32	1,326,000	1,052,000	1,704,000	11.82	55.01
1990	1,766,000	1,545,000	2,086,000	7.81	1,131,000	910,000	1,451,000	12.19	35.94
1991	2,144,000	1,853,000	2,542,000	7.83	1,368,000	1,077,000	1,766,000	12.27	36.22
1992	2,004,000	1,683,000	2,363,000	8.14	1,335,000	1,014,000	1,694,000	12.23	33.39
1993	1,504,000	1,247,000	1,860,000	10.40	1,258,000	1,001,000	1,614,000	12.43	16.37
1994	2,203,000	1,784,000	2,805,000	11.66	1,811,000	1,393,000	2,413,000	14.17	17.76
1995	3,388,000	2,972,000	4,097,000	9.53	2,450,000	2,034,000	3,159,000	13.18	27.68
1996	2,795,000	2,305,000	3,483,000	10.57	2,009,000	1,519,000	2,698,000	14.70	28.11
1997	1,633,000	1,469,000	1,933,000	8.27	1,308,000	1,143,000	1,607,000	10.34	19.94
1998	1,062,000	945,000	1,279,000	9.70	947,000	830,000	1,164,000	10.87	10.82
1999	1,116,000	998,000	1,335,000	9.87	1,016,000	898,000	1,234,000	10.84	8.97

Table 1.5. Sensitivity to alternative weighting values. Seven different trials for each river are shown to illustrate the relative effects of changing weights on the four datasets. E is escapement, C is commercial catch and effort, T is test-fish, and S is whole river sonar. Mean squared error (MSE) is defined for each of the four datasets. MPD is the mean percentage difference from the base case (BASE = preferred weighting values) scenario and MAPE is the mean absolute percentage error from the base case. We show this difference for the average of the abundance, $\hat{\bar{N}}$, and escapement, $\hat{\bar{E}}$, estimates over all years and for the escapement scaling parameter, $\hat{k}_E$. Differences were negligible for other model parameters.

Trial	Weighting Values				Mean Squared Error				$\hat{\bar{N}}$		$\hat{\bar{E}}$		$\hat{k}_E$
Kuskokwim	E	C	T	S	MSE_E	MSE_C	MSE_T	MSE_S	MPD	MAPE	MPD	MAPE	MPD
BASE	1	1	0.3	1	0.029	0.380	0.718	0.004	0%	0%	0%	0%	0%
1	1	1	1	1	0.089	0.392	0.590	0.011	7%	8%	12%	14%	11%
2	5	1	1	1	0.009	0.408	0.731	0.012	2%	4%	5%	9%	5%
3	1	5	1	1	0.124	0.350	0.638	0.029	12%	14%	23%	27%	21%
4	1	1	5	1	0.320	0.437	0.435	0.088	30%	33%	55%	62%	41%
5	1	1	1	5	0.092	0.395	0.602	0.001	1%	6%	0%	11%	-1%
6	1	1	1	0.2	0.089	0.387	0.559	0.108	26%	26%	51%	51%	50%
7	1	1	0.1	1	0.014	0.378	0.806	0.003	-3%	3%	-4%	5%	-5%
Yukon	E	C	T	S	MSE_E	MSE_C	MSE_T	MSE_S	MPD	MAPE	MPD	MAPE	MPD
BASE	3	0.3	0.3	1	0.01	0.94	0.48	0.01	0%	0%	0%	0%	0%
1	1	1	1	1	0.06	0.81	0.47	0.01	-8%	12%	-12%	19%	-100%
2	5	1	1	1	0.01	0.87	0.48	0.04	-9%	11%	-14%	16%	-81%
3	2	0.5	1	1	0.02	0.90	0.45	0.01	-7%	8%	-11%	13%	-59%
4	5	0.2	1	1	0.00	1.02	0.46	0.01	4%	5%	6%	7%	32%
5	3	0.3	1	1	0.01	0.96	0.45	0.01	-2%	3%	-4%	5%	-13%
6	3	0.3	0.3	0.2	0.00	0.88	0.49	0.08	-11%	14%	-18%	20%	-92%
7	3	0.3	0.3	3	0.01	0.97	0.48	0.00	4%	5%	6%	7%	32%

2 Pacific Salmon Abundance and Escapement Estimates in Data-Limited Situations: Robustness to Measurement Error [2]

2.1 Abstract

Novel techniques for salmon abundance and escapement estimation in data limited regions (Chapter 1) require some assessment of the effect of measurement error on the estimation process. We used data from a salmon stock where abundance and escapement were well known (Ugashik River, Bristol Bay, Alaska) and applied the same statistical framework used in our previous estimation of Kuskokwim and Yukon River summer chum salmon to determine whether this process could reproduce the true population estimates and parameters. We considered robustness by simulating various typically reported levels of measurement error on the escapement index and sonar data. Standardized true escapement formed the escapement index and various three year combinations of true abundance data emulated the limited sonar information available from previously studied systems.

Performance measures of bias and accuracy were calculated over twenty measurement error scenarios. Increases in error in abundance data had negligible effect on all estimates, and abundance estimation was fairly robust to all error scenarios. Effects of increasing error in the escapement index were confounded with the particular

[2] Authors: S. Kalei Shotwell and Milo D. Adkison. Journal considered for publication: Transactions of the American Fisheries Society. To be submitted.

abundance sequence used; we, therefore, summarized performance by each specific combination of years. Poor combinations resulted in high levels of bias, which masked the ability of the modeling process to produce reliable escapement estimates. Good sequences resulted in low bias overall even under high levels of escapement error. We identified the cause for good and poor abundance combinations as a poor estimate of the catchability coefficient which forced large upward biases in the escapement estimates. Effort data were fairly limited in our known system creating two regimes in the frequency of reported landings by opening. This forced different interpretations of effort throughout the time series and poor performance was observed when the model relied more on the catch and effort dataset. Specific properties of the three-year abundance combinations that produced good versus poor estimates were difficult to identify. However, we recommend that managers select abundance estimates with good contrast between years and good agreement between run timing of associated catch and effort data for those years. A full simulation may better identify particular caveats of measurement error within each of the potential datasets used in this modeling framework.

2.2 Introduction

Successful management of fisheries with limited population information requires creative techniques for quantitative stock assessment. For data-limited stocks of Pacific salmon, top priority is to develop methodologies for abundance and escapement estimation to then define a spawner-recruit relationship and inform harvest management (Quinn and Deriso 1999). We developed a statistical modeling framework that simultaneously combined various data sources to arrive at these estimates (Shotwell and Adkison *in press*). Our procedure dealt with the often sparse escapement data from these systems by developing an escapement index rather than simply pooling the available escapement data. For the situation where a variety of escapement tributary counts exist for one river system, we utilized the pattern extraction qualities of principal components analysis (PCA) to derive this index.

As with any model there are various assumptions made throughout the development that affect the final product and bring about an element of uncertainty. In Shotwell and Adkison (*in press*), we used a somewhat arbitrary weighting scheme to reflect our relative confidence in each of the various types of data used. It is often assumed that catch data contains insignificant amounts of measurement error, but that escapement data can rarely be collected without large sampling errors (Walters and Ludwig 1981). In this study, we consider the implications of potentially large amounts of measurement error propagating through the escapement information in our modeling process.

In our previous paper (Shotwell and Adkison *in press*, Chapter 1), we developed the escapement index from tributary monitoring surveys, some of which are believed to contain large amounts of measurement error (Clark 2001). In particular, aerial surveys were the dominant form of escapement monitoring in our case study as they are practical for regions with large numbers of tributaries within one river system (Jones et al. 1998). These survey counts are subject to substantial amounts of measurement error due to differences in weather conditions, pilot and observer experience, water properties (glare, clarity), and timing of surveys (Parken et al. 2003). Even though the use of PCA to extract a common temporal pattern across multiple systems might buffer the influence of individual tributary measurement error in the escapement index, a large amount of uncertainty may still be incorporated into the escapement estimates.

Our approach also relied heavily on the inclusion of whole river sonar enumeration of escapement, added to catch data, to provide total abundance estimates for at least a few years. Otherwise, confounding occurred between the scaling parameters and the abundance estimates. This dependence transferred any uncertainty in the sonar information to the model estimates. Common sources of error in sonar counting are incorrect species apportionment, poor site selection, substrate avoidance or repeated passage by fish, accumulated debris around the machine, and imprecise machine calibration or adjustments (Cousens et al. 1982). It is also unknown what effect the total available number of sonar years or a particular combination of sonar years may have on the estimation of scaling parameters. This could be important when the abundance and escapement estimates are highly variable over time.

This study is designed to assess the robustness of our salmon abundance estimation methodology to measurement error in the data to provide managers with an idea of the reliability of the estimates generated through our methods (Ludwig and Walters 1981). Our approach is to apply our methodology to a salmon stock where escapement and abundance are fairly well known and then determine whether the modeling framework can reproduce the true population estimates and parameters. To replicate a situation where data are limited and of poor quality, we pretend that escapement data are available only as an index and that abundance data exist for only a few years. We superimpose random errors on these limited data.

An understanding of the effects of measurement error within a system is vital for formulating appropriate management decisions. Our objectives in this analysis are to determine 1) whether our modeling framework produces reliable estimates of abundance and escapement under typical levels of measurement error, 2) whether high levels of bias result from increasing measurement error, and 3) whether the number or sequence of years of abundance data influences the effect of measurement error on the estimates. We use sockeye salmon (*Oncorhynchus nerka*) data from the Ugashik River, Bristol Bay, where total abundance and escapement are known (Figure 2.1).

2.2.1 System History

Bristol Bay is made up of eight major river systems that collectively provide for the largest commercial sockeye salmon fishery in the world (Weiland et al. 2003). Commercial harvests are directed at terminal areas near the river mouths and the spawning escapement goals for each stock are based on maximum sustained yield (Weiland et al. 2003). The region is divided into five management districts and only Ugashik, Egegik, and Togiak are assumed individual stocks, where the stock from only one river is harvested in the terminal area of that district (L. Fair, Alaska Dept. of Fish and Game, personal communication). Subsistence harvests of sockeye are minor compared to commercial harvests throughout the region. Escapement is typically estimated through counting towers located up river from the commercial fishery. Test fisheries are primarily used as an inseason estimate of the number of fish between the commercial fishery and counting towers and not as a measure of total abundance (L. Fair, Alaska Dept. of Fish and Game, personal communication).

The Ugashik district is a good system to test the assumptions of our statistical framework. This is a single stock fishery where nearly all the commercial salmon harvest in this district is sockeye salmon (Weiland et al. 2003). This limits potential issues with species misallocation. Commercial sockeye salmon harvests for Ugashik are similar in magnitude to the sockeye escapements. This prevents the commercial harvests from overwhelming the escapements which can be problematic in estimating variability in escapement over time (Shotwell and Adkison *in press*). Also, there is relatively high confidence in the escapement data (L. Fair, Alaska Dept. of Fish and Game, personal communication).

In the Ugashik River, sockeye enter the district in early June and peak during the middle of July. At the onset of the return, migration from the district to the lake system may take about a week while during the peak season it may take one to two days. Spawning lasts from late July through September and peaks in mid August. Ugashik sockeye typically spend two to four years in freshwater, including the first year spent in the gravel (F. West, Alaska Dept. of Fish and Game, personal communication). We apply our procedures to commercial fishery data and escapement counts from this system to test the robustness of our methods and assess the effects of potential measurement error in the sonar data and escapement index.

2.3 Methods

2.3.1 Data Used

The Ugashik district is located in the Bristol Bay management area (Figure 2.1) part of the ADFG Division of Commercial Fisheries Region 2 (Central Region). The primary sources for data used in this investigation were the Bristol Bay Annual Management Reports (AMRs) produced by the ADFG Division of Commercial Fisheries. We also received data directly from several area research biologists (L. Fair and F. West, Alaska Dept. of Fish and Game, personal communication). Unlike the Yukon and Kuskokwim drainages, where we first applied our methodology, subsistence harvest is minimal and thus ignored in the abundance estimates for this region. Also, test fisheries for this region are not designed to provide an index of abundance as catch per unit of effort (CPUE). The values of test fishery CPUE are thus difficult to interpret (L. Fair, Alaska Dept. of Fish and Game, personal communication) so we did not consider the test-fish data in this study.

We collected all available escapement and commercial fisheries data for the Ugashik district. Escapement counts existed as whole river enumerations from towers over the period 1956-2003. Annual and daily commercial harvests were also recorded from 1956-2003. However, commercial effort data was fairly limited. We desired to remain consistent with the methodology employed for the Yukon and Kuskokwim drainages in defining effort as the number of permits multiplied by the hours fished. Unfortunately, over the years 1978-1992 aerial surveys were used to estimate the number of boats on the fishing grounds only as time permitted, producing fairly infrequent effort estimates throughout these seasons. No effort data exist in the AMRs prior to 1966 and for 1972-1973. This left only twenty-one years with fairly complete effort data: 1966-1971, 1974-1977, and 1993-2003. Fortunately, this was a similar number of years to those available in the case studies of the Kuskokwim and Yukon Rivers (25 years). We used abundance, escapement (Figures 2.2a & 2.2b), and commercial catch and effort (Figures 2.3a & 2.3b) for the years when effort data was available.

2.3.2 Abundance and Escapement Model

In this study, we applied the methodology of Shotwell and Adkison (*in press*), with a few minor differences, to the available data on Ugashik district sockeye salmon. As explained previously, no subsistence, test-fish, or sonar data exist for this district, and effort data were limited. However, unlike the Yukon and Kuskokwim drainages where this methodology was first applied, total abundance and escapement are measured fairly accurately each year. To simulate a situation where escapement data were only an index of abundance, we created an escapement index by standardizing (subtracting the mean and dividing by the standard deviation) the true escapement time series. Also, we pretended we had absolute abundance estimates for only a few of the 21 years. Annual catch was assumed to be measured each year with negligible error (Walters and Ludwig 1981). This scenario (catch fairly well known, escapement available only as an index, few total abundance estimates) is typical of many salmon stocks, in particular the Kuskokwim and Yukon Rivers.

Model equations were identical to those of Shotwell and Adkison (*in press*), except that a prediction of test fishery CPUE was not generated. Parameters estimated were the run timing parameters, $\hat{D}$ and $\hat{\omega}$, the catchability coefficient, $\hat{q}$, the escapement index scaling constants, $\hat{k}_E$ and $\hat{K}$, and the set of abundance estimates, $\hat{N}_y$. Weights for each dataset were equal, so the likelihood equation simplified to the following:

(1)
$$\ln \mathrm{L} \propto \frac{1}{n_e}\sum_y \left(\ln\left(E_y\right)-\ln\left(\hat{E}_y\right)\right)^2 + \frac{1}{n_c}\sum_y \sum_d \left[\ln\left(C_{y,d}\right)-\ln\left(\hat{C}_{y,d}\right)\right]^2 + \frac{1}{n_s}\sum_y \left(\ln\left(N_y\right)-\ln\left(\hat{N}_y\right)\right)^2$$

In this equation, E is the annual index of escapement, C is commercial catch by year and statistical week, and N is total abundance. Each sum of squares is divided by the appropriate n, the total number of data values, so that each data type has equal weighting.

2.3.3 *Robustness Tests*

We simulated several levels of measurement error in both the escapement index and abundance data to emulate values reported for salmon stocks. Indices of escapement are commonly obtained from aerial surveys, although tower and weir counts of certain tributaries are sometimes used. Coefficients of variation (CVs) for escapement estimation methods using aerial survey counts are 10-90% (Jones et al. 1998, Parken et al. 2003). Estimates of total abundance depend on adding catch estimates to an enumeration of escapement for the whole drainage, often obtained by sonar. Accuracy of sonar counts is estimated to be 2-15% on average (Cousens et al. 1982, C. Pfisterer, Alaska Dept. of Fish and Game, personal communication). However, this may be an understatement of error.

Typical errors, such as large amounts of fish distorting an individual signal or species misidentification, are often not easily quantified. We, therefore, simulated CVs of 0%, 10%, 25%, 50%, and 80% for the escapement index and CVs of 0%, 5%, 10%, and 25% for the abundance data in this analysis.

Prior to any measurement error simulations, we first considered the effect of the number of available years of abundance estimates. We used all possible combinations of one, two, and three abundance years in the model, adding no measurement error to either the escapement index or abundance data (Table 2.1). We restricted the total number of combinations to only three years because this was the least amount of years available in the previous case study on the Kuskokwim and Yukon Rivers (Shotwell and Adkison *in press*). We recorded the resulting abundance and escapement estimates and other model parameters for each of the 1,561 combinations.

For trials with measurement error, we explored five different three-year sequences of abundance data (Table 2.1). We chose subsets that were simple three-year sequences (e.g., 2001, 2002, 2003) because a typical sonar program would most likely operate for several years in a row rather than non-sequentially. We also chose only three years because we again desired to replicate the lower number of available years in our previous case study on the Kuskokwim and Yukon Rivers (Shotwell and Adkison *in press*). The five subsets were selected to cover the entire time series as evenly as possible (Fig 2.2a).

We then used the following relationship between CV and the variance of error term (σ) to include various levels of measurement error in both the escapement index and the three sequential years of abundance data (MacGregor et al. 2002):

(2) $$\sigma^2 = \ln(\mathrm{CV}^2 + 1)$$

This variance was then multiplied by a normal random number to generate smeared values of escapement (E_y) and abundance (N_y) data as in the following equations:

(3) $$E_y = E_{y,true} * \exp\left(r_y\right),\ r_y \sim N\left(0, \sigma_r^2\right)$$

(4) $$N_t = N_{t,true} * \exp\left(v_t\right),\ v_t \sim N\left(0, \sigma_v^2\right).$$

Here $E_{y,true}$ and $N_{t,true}$ are the true values of escapement and abundance over all years (y) or a particular sequence of years (t) while r_y and v_t are the random variables drawn from a normal distribution with mean zero and variance σ_r^2 and σ_{v}^2. The escapement index was then constructed by standardizing the smeared values of escapement (E_y) over the time series.

Simulations were performed on each smeared pair of escapement and abundance data creating twenty measurement error combinations each with five three-year sequences of abundance data, for a total of 100 scenarios. We then generated two groups of 100 sets of random numbers (r_y and v_t). For each of the 100 scenarios, each of these sets of random numbers was used to simulate smeared escapement and abundance data using equations 3 and 4 (simulations per se were not necessary for the five scenarios where all measurement errors were zero).

2.3.4 Performance Measures

For each model run, we recorded abundance and escapement estimates along with the values of the other model parameters. This resulted in 100 records for each scenario (the particular three-year sequence and measurement error combination). We compared the 100 records for each scenario with the true values of abundance and escapement by calculating two performance measures for error analysis, bias and accuracy. Both of these are based on residuals of the predicted abundance and escapement estimates relative to the true values of abundance or escapement as:

$$(5) \qquad r_y = \frac{\hat{x}_y - x_{y,true}}{x_{y,true}}$$

where r_y is the residual by year, $\hat{x}_y$ and x_{true} are the predicted and true value, respectively for either the abundance or escapement estimates. To quantify bias we calculated the average of these yearly residuals over the time series of abundance or escapement and then averaged these values by scenario. Our measure of accuracy was simply the standard deviation of the same yearly residuals used for the bias measure. This is basically a coefficient of variation (CV). We also averaged these values by scenario for both abundance and escapement estimates. Both bias and accuracy were expressed as percents and large values for both measures indicate poor estimates of the true values.

We explored the effect of the different years of abundance data by summarizing the performance measures for each of the five three-year sequences within each measurement error pair (Table 2.1). Sensitivity of the model to increasing measurement error was determined by the degree of increase in bias and accuracy with respect to increasing measurement error on either the escapement index or the three-year abundance combination. Model residual sum of squares were recorded for each trial to check for failures in the estimation algorithm.

2.4 Results

Bias and accuracy were larger for escapement than abundance estimates over all possible combinations of one, two and three years of abundance data (Table 2.2, total of 1,561 simulations). Bias was substantially reduced as the number of years of abundance data increased; however, the reduction in the accuracy of estimates was smaller (Table 2.2). The lowest model accuracy was 16% and 21% for the abundance and escapement estimates, respectively. A large range of parameter values were estimated for the catchability coefficient $\hat{q}$ and the escapement scalars $\hat{k}_E$ and $\hat{K}$ over all possible combinations of three years. This may indicate that the particular sequence of years substantially affects the estimation process.

In several trials, the parameter estimation algorithm failed to find a solution (total failures = 665). In these instances, the specific parameters that could not be estimated were the scalar on escapement ($\hat{k}_E$) and escapement estimates for at least one of the years 1967, 1968, 1969 and 1995. These failures typically occurred with high levels of simulated escapement error. The results of these trials were not included in calculations of the performance measures.

The effect of increased error in the data was confounded to a large degree by the particular three-year combination for which abundance was assumed known. We therefore summarized the performance measures separately for each of the five three-year combinations. We classified a scenario as a good result if bias was relatively low overall measurement error levels. High bias will skew the interpretation of the accuracy performance measure; therefore, scenarios containing high bias over all measurement error levels were considered poor results. Scenarios with good results were the three-year combination numbers 2, 4, and 5, while poor scenarios were 1 and 3 (Table 2.3). For the most part, bias increased and accuracy decreased for both the abundance and escapement estimates as either type of measurement error increased (Table 2.3). However, these changes due to measurement error level were substantially smaller than differences resulting from the particular three-year combination (Table 2.3).

We present the results of increasing levels of measurement error over a representative combination of both a good and poor scenario. The second combination, years 1975, 1976, and 1977, was an example of a good sequence (Table 2.3). Bias was relatively small (~8% or less on average) for both the abundance and escapement estimates over all combinations of measurement error (Figure 2.4a). The accuracy of the abundance estimates was fairly low over all simulations (~31% or less on average, Figure 2.4b). However, accuracy of the escapement estimates was larger (~61% or less on average, Figure 2.4b) over all simulations. In this case, the model performed well under high levels of escapement error. Measurement error in the abundance data had a negligible effect on the measures of bias and accuracy (Figures 2.4a & 2.4b).

On the other hand, the first combination, years 1968, 1969, and 1970, constituted a very poor sequence of years. Bias and accuracy were higher for the abundance estimates (40% and 50% or less, Figures 2.5a & 2.5b) but relatively consistent over increasing measurement error as with the previous scenario. However, performance of the escapement estimates was very poor (~87% and ~91% or less for bias and accuracy, respectively). Bias decreased to ~45% with higher levels of escapement error (Figure 2.5a) while accuracy increased over all levels of escapement error level (67% on average to 91% on average, Figure 2.5b). In this scenario, the modeling process did very little to counteract the effects of increased measurement error. Again, the different measurement error levels on abundance data had negligible effect on either performance measure (Figures 2.5a & 2.5b).

The remaining combinations fell somewhere in between these two extremes. Combinations 4 and 5 (good scenarios) also had relative low bias, but accuracy was much higher for both abundance and escapement estimates. Combination 3 (poor scenario) contained similar levels of bias and accuracy as that of combination 1 but there was a noticeable effect of changing measurement error on the abundance data.

2.4.1 Effect of Additional Data Sources

To clarify the dependence of the model on the particular sequence of abundance years, we first explored the parameter estimates within the model, in particular the estimates that relate to the additional data sources, catch and effort. The pattern between the catchability coefficient ($\hat{q}$) and escapement scalar mean ($\hat{K}$) over all simulations (Figure 2.6a) demonstrated that underestimates of $\hat{q}$ forced upward bias in the escapement estimates (as we might expect, since lower fleet efficiency produces lower catch and hence higher escapement). There was also a fairly well defined negative relationship between $\hat{q}$ and the run timing standard deviation, $\hat{\omega}$ (Figure 2.6b). We found that a basic difference between good and poor combinations occurred in the model parameters of these scenarios. Parameters of good combinations were nearer the true values and little overall bias was detected in the estimates. Poor combinations underestimated catchability and slightly overestimated run timing forcing a large upward bias on the escapement estimates. Sensitivity of the model depended on the interaction between the measured escapement index and the auxiliary data in the model.

To determine what property of the three-year abundance combination produced these poor estimates, we examined the relationship between the true abundance and catch per unit of effort (CPUE, Figure 2.7). Effort data were not fixed from year to year in this system; therefore, the relationship between abundance and CPUE is not necessarily linear (Quinn and Deriso 1999). A nonlinear relationship does seem more appropriate based on the data in the Ugashik system and the catch equation in our modeling framework allowed this type of relationship. There did seem to be a general difference between some good (scenarios 4, and 5) and poor (scenarios 1 and 3) combinations, where the former contained more contrast in the three-year abundance combination than that latter. However, the dependence on data contrast did not hold for all possible three-year abundance combinations (results from initial no error added simulations, total of 1,561).

Finally we considered the fit of the catch data in relation to the catchability coefficient, $\hat{q}$, to determine the relative importance of this dataset when catchability was underestimated. In general, as model fit to the catch and effort data improved, catchability was underestimated; therefore, high levels of bias were associated with more reliance of the model on the catch and effort data. This was also consistent with all possible three-year abundance combinations under no error.

2.5 Discussion

We explored the robustness of our modeling process to measurement error in both the escapement index and abundance data by simulating varying degrees of error on information from a data-rich stock, Ugashik River sockeye salmon. Multiple simulations using only a subset of the available abundance data and an index of escapement, with varying amounts of simulated measurement error, were fed to the model along with known catch and effort data to produce abundance and escapement estimates. These results were then compared to the true abundance and escapement through performance measures of bias and accuracy.

Our objectives were to determine whether our modeling process produced relatively unbiased results that reflected the true population parameters under high levels of measurement error in both the escapement index and abundance data. We found that typical levels of measurement error in abundance had little effect on the estimates. The effect of measurement error on escapement, on the other hand, was highly confounded with the combination of abundance years. Particular combinations of years of available abundance data produced very poor estimates of abundance and escapement.

Although all combinations yielded increased accuracy on the escapement estimates with increasing escapement error, three combinations were considered good because they had relatively low or negligible bias overall. The sensitivity of the modeling process to high levels of escapement error is best defined by these combinations (Hilborn and Walters 1992). With some good combinations the model performed well under very high levels of escapement error. The principal difference between good and poor combinations of abundance was the estimate of the catchability coefficient. Poor combinations consistently underestimated this parameter resulting in large overestimation of the escapement scalar and extreme bias. When parameters are highly biased the precision measure of a model process is not easily defined and it becomes difficult to assess how robust the modeling process can be to high levels of error (Sokal and Rohlf 1995, Hilborn and Walters 1992). It is clear that the modeling process is extremely sensitive to specific properties of the three-year combination of abundance. Performance may partially depend on the agreement between the abundance combination and the auxiliary data in the model.

In our known system, the relationship between the year's average CPUE and true abundance was poorly defined. As expected from the fairly limited effort data for Ugashik River sockeye salmon, the amount of variability explained through the catchability relationship was very low. It is likely that in this case the effort data was poor and did not aid the modeling process toward estimating true escapement when the escapement index was relatively well known (i.e., low escapement CV). However, it did help to some extent when the escapement index was very poor, indicating that the modeling process will help in these situations. This pinpoints a major consideration on the reliability of effort data within the modeling framework. As in many systems, reported measures of effort improve over the existence of the fishery. In the Ugashik system (and the rest of Bristol Bay), effort for the early years (1966 through 1977) was reported by opening (in days) with limited season coverage, whereas effort over the later years (1993 through 2003) was recorded daily and landings were well covered over the season. Our measure of effort as permits times hours open has different implications under these two regimes of reported effort. For example, fishermen are generally not able to fish for five days straight, but the hours open for the fishery may be five days or 120 hours. Landings in the early years were only reported for the five day opening. Landings in the later years were reported daily. We will consistently underestimate CPUE and therefore catchability for the early years but not for the later years. Therefore, the catch data will most likely not be fit well by the model and the more the model must rely on this information the higher the bias and accuracy.

The specific properties of the three-year abundance combination that produced good or poor escapement estimates were difficult to identify. High levels of contrast in abundance between the three years were not consistent over all combinations, even though in some cases this did seem to indicate a good or poor year. In this system, the effort data were not reliable across the time series and this produced large disagreements between the datasets. In general, the model did not fit the catch data well; however, this was consistently more pronounced with good combinations. Finally, the standard deviation of run timing was slightly lower in good versus poor combinations, which suggests that run timing of the particular three-years used for abundance is more in agreement for good scenarios. We find this to be consistent over the seasonal distribution of observed catch and effort for the five three-year combinations used in our measurement error simulations. It seems that good contrast in abundance data, less reliance on the catch relationship, and more certainty about the run timing all at least partially explain the reason for good versus poor combinations.

With these limitations in mind, it may be a better test to construct a full simulation of all data within this modeling framework to distinguish the different effects of measurement error on any one data source to the estimation of parameters. However, with this less complicated example, we were able to demonstrate that the model is fairly robust to abundance estimation and measurement error in sonar data. Escapement estimation improves under high levels of measurement error when the sequence of abundance years provides a good estimate of catchability. Therefore, estimated recruits (as measured by abundance) from our model are robust to changes in measurement error, and confidence about the number of estimated spawners (escapement) depends largely on the three-year abundance combination. In general, we recommend that managers considering this modeling framework for future stock assessment choose measures of abundance that exhibit some contrast from year to year and correspond to catch and effort data with consistent run timing. In combination, these properties may help alleviate the dependence on the particular combination of abundance years. Another option would be to consider whether additional abundance years lower the initial bias and how many are required to reduce the high sensitivity of this model to a particular combination. Again a full simulation would be more appropriate for this type of investigation.

Finally, we believe the confounding effect of poor effort data on performance is particularly notable. Reliability of this information as pertains to the consistent interpretation of a measure of effort throughout the history of a fishery is not often considered in traditional stock assessment of Pacific salmon. Specifically we recommend that managers use a measure of effort that is consistent in the frequency of reports throughout the fishing season. Future investigations should expound on this example by generating a complete simulation that includes measurement error on both the catch and effort data.

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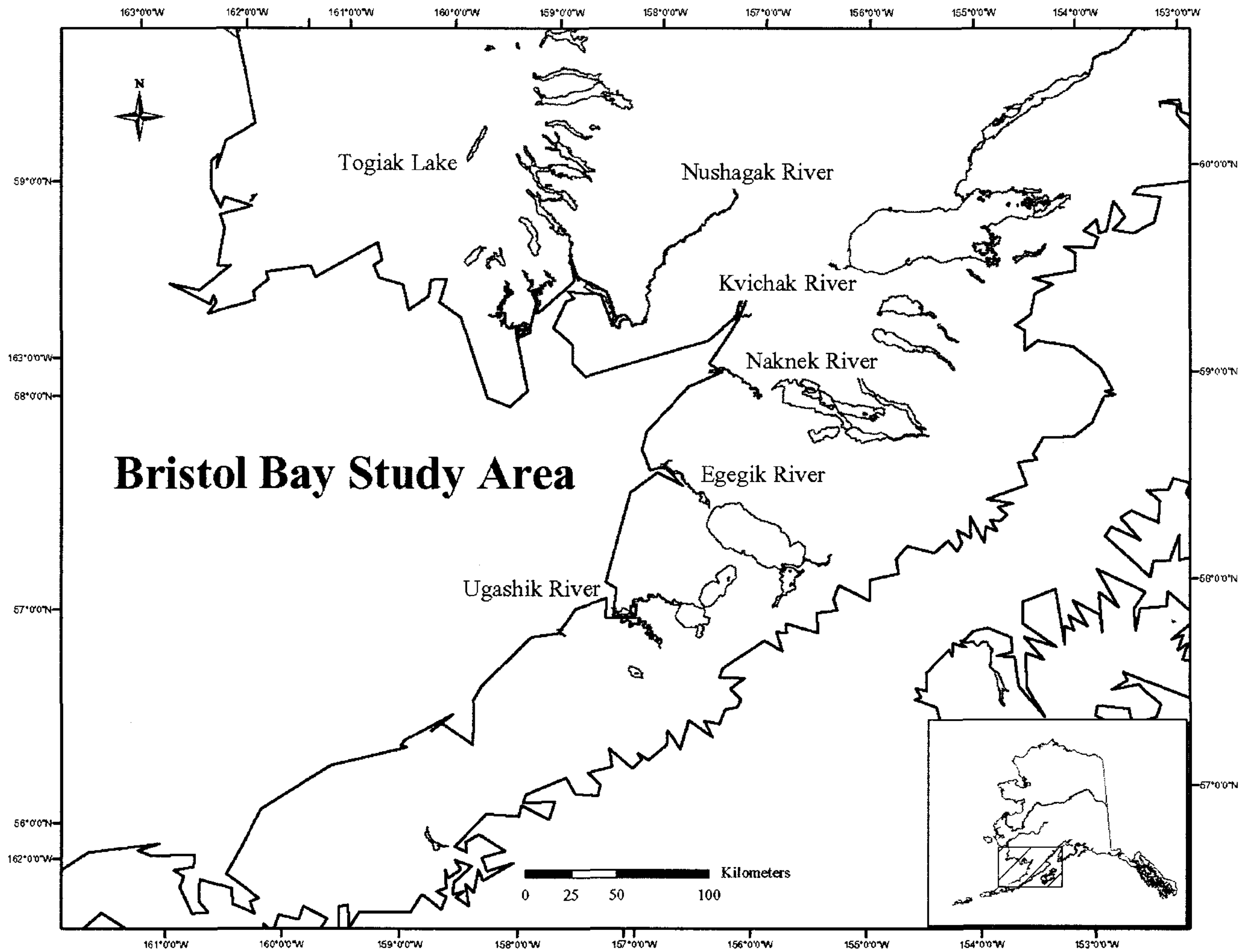
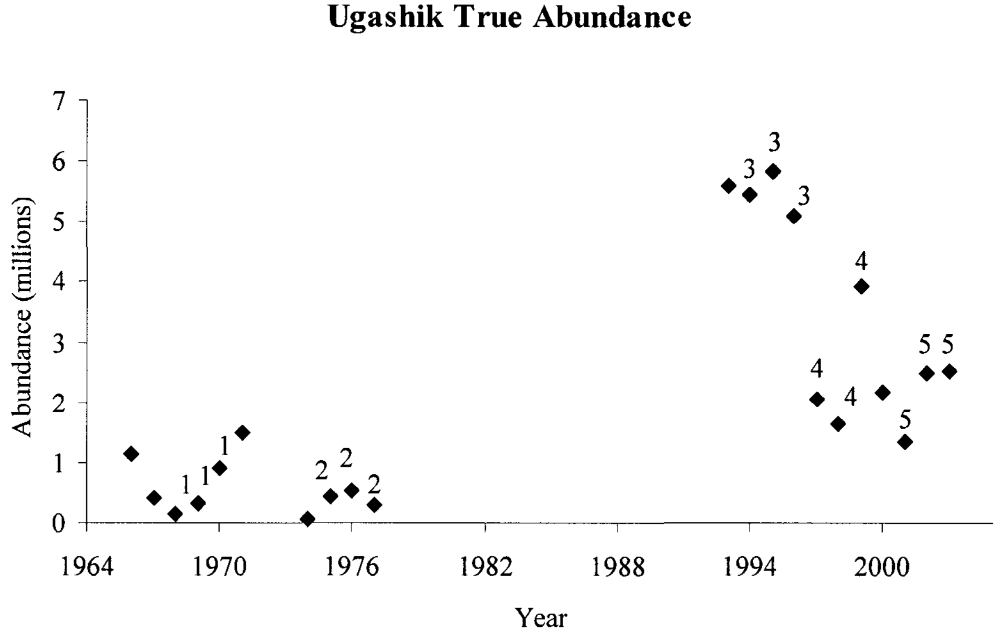


Figure 2.1. Map of Bristol Bay study area.

a)



b)

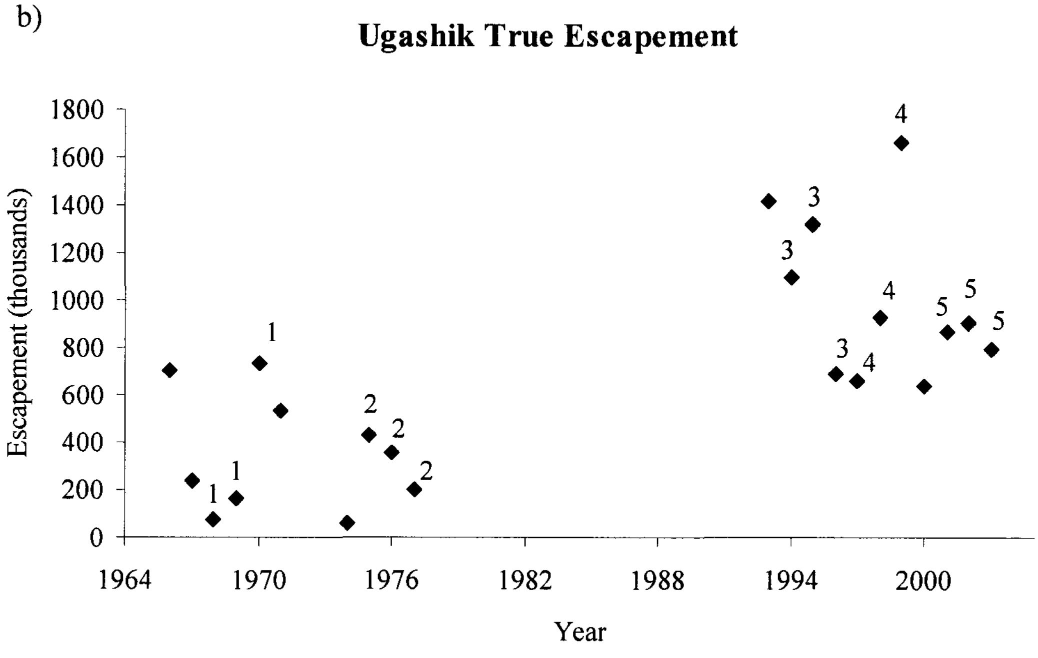


Figure 2.2: Time series of true abundance (a) and escapement (b) for Ugashik River sockeye salmon from 1966-1971, 1974-1977, and 1993-2003. Numbers above data points correspond to particular combination of abundance years (Table 2.1).

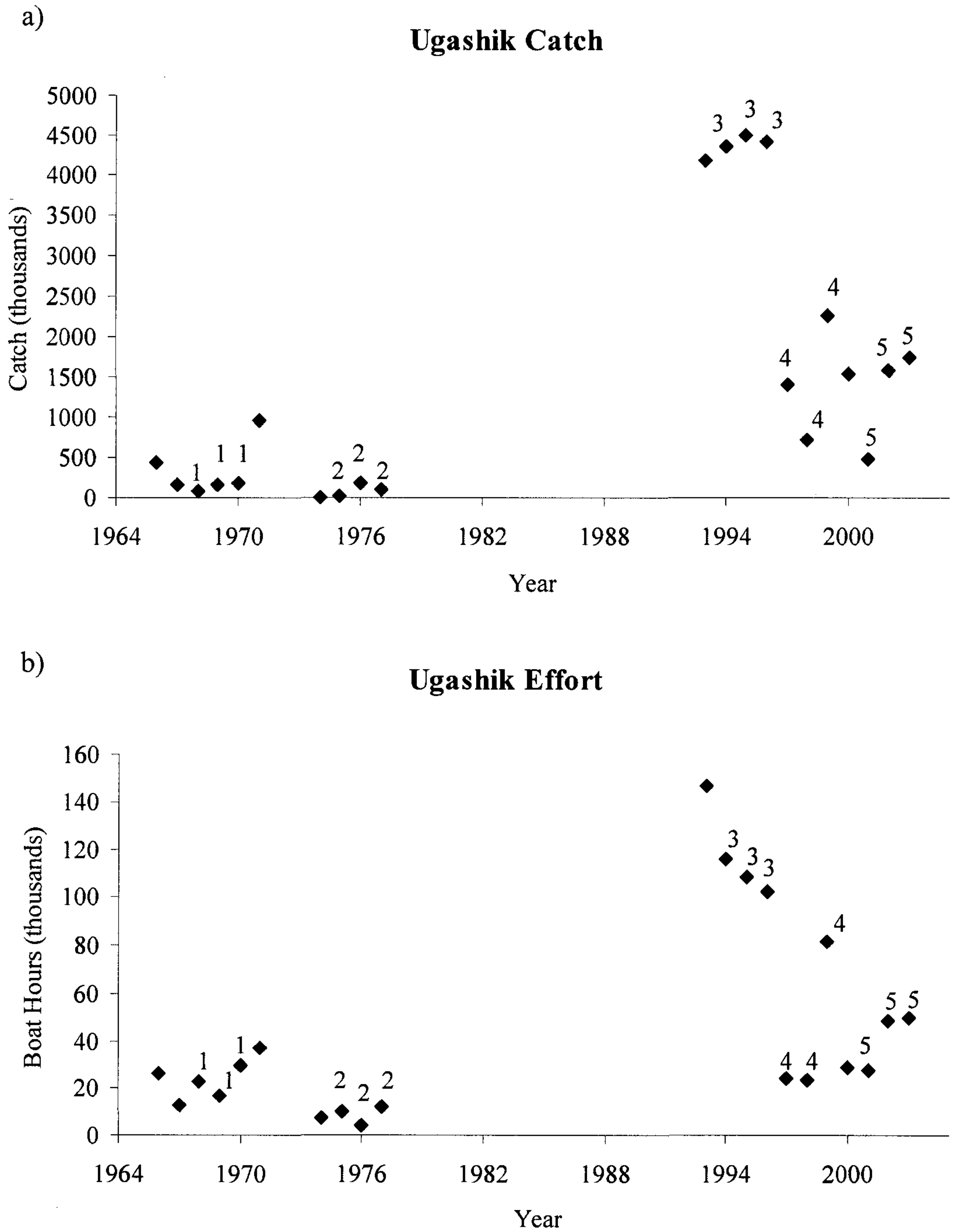


Figure 2.3: Time series of catch (a) and effort (b) for Ugashik River sockeye salmon from 1966-1971, 1974-1977, and 1993-2003. Numbers above data points correspond to particular combination of abundance years (Table 2.1).

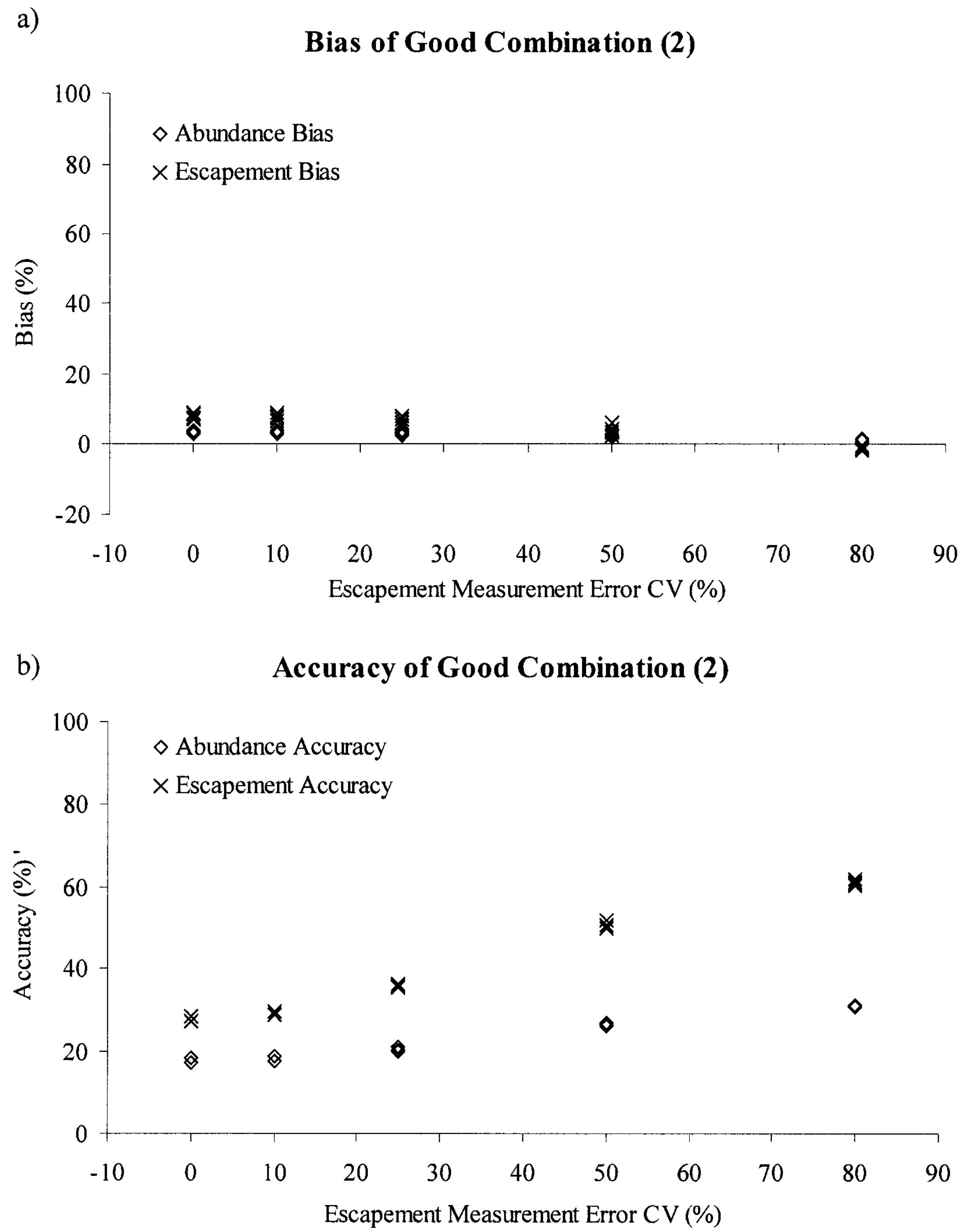


Figure 2.4: Performance measures for Combination 2 (1975, 1976, 1977) along increasing escapement error levels. (a) Bias in percent for abundance (open diamonds) and escapement (x's) estimates and (b) accuracy in percent for abundance (open diamonds) and escapement (x's) estimates. Four diamonds or x's occur at each escapement error level representing changing abundance error.

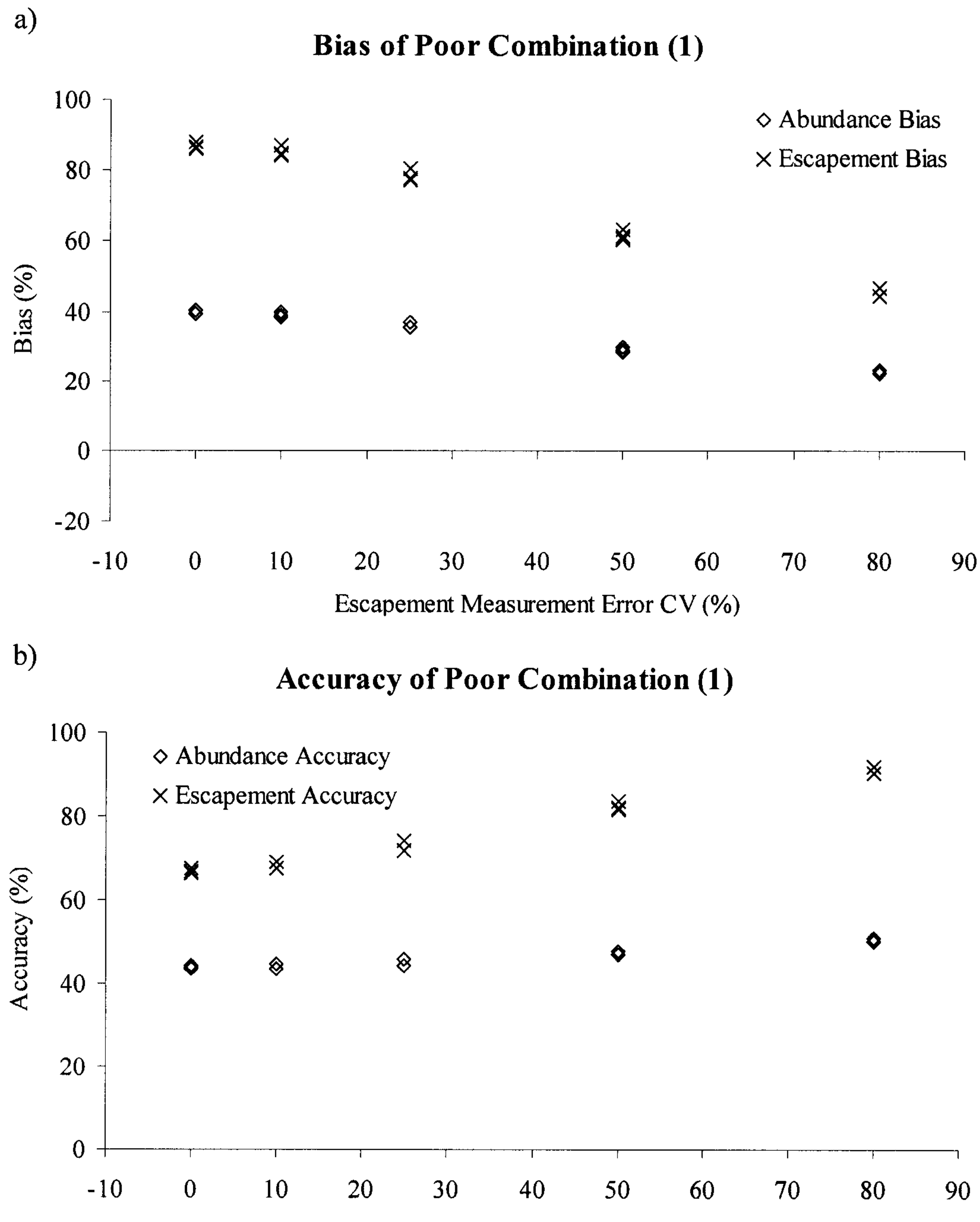
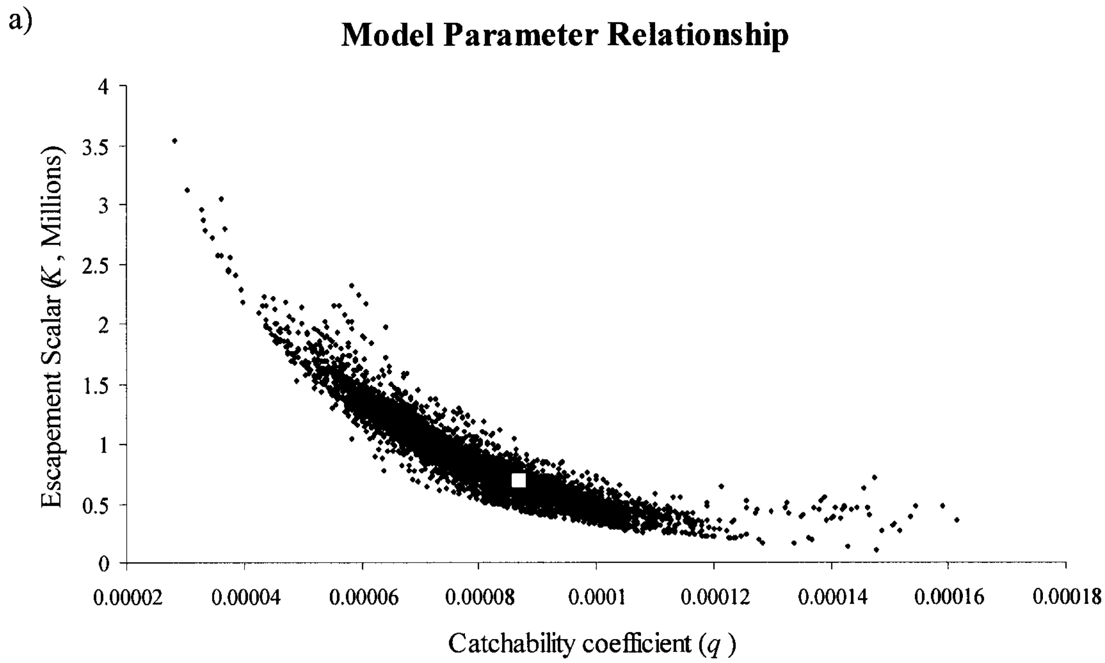


Figure 2.5: Performance measures for Combination 1 (1968, 1969, 1970) along increasing escapement error levels. (a) Bias in percent for abundance (open diamonds) and escapement (x's) estimates and (b) accuracy in percent for abundance (open diamonds) and escapement (x's) estimates. Four diamonds or x's occur at each escapement error level representing changing abundance error.



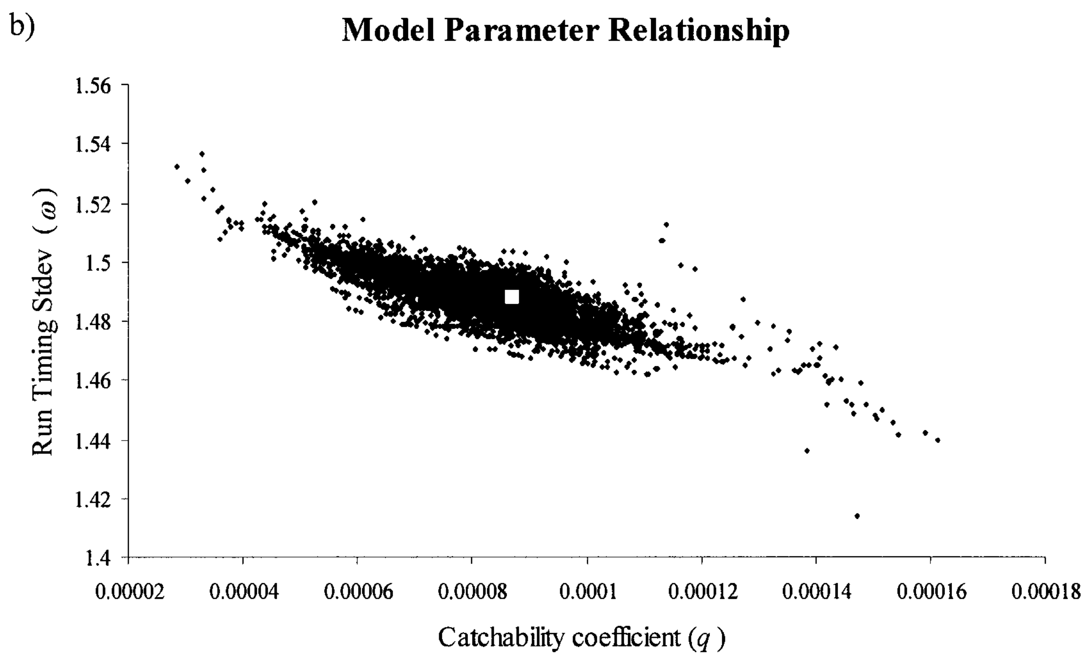


Figure 2.6. Model parameter relationships. Catchability coefficient ($\hat{q}$) estimates versus a.) escapement scalar ($\hat{K}$) estimates and b.) run timing standard deviation ($\hat{\omega}$) over all simulations of measurement error. White square in center of data cluster is the true parameter value.

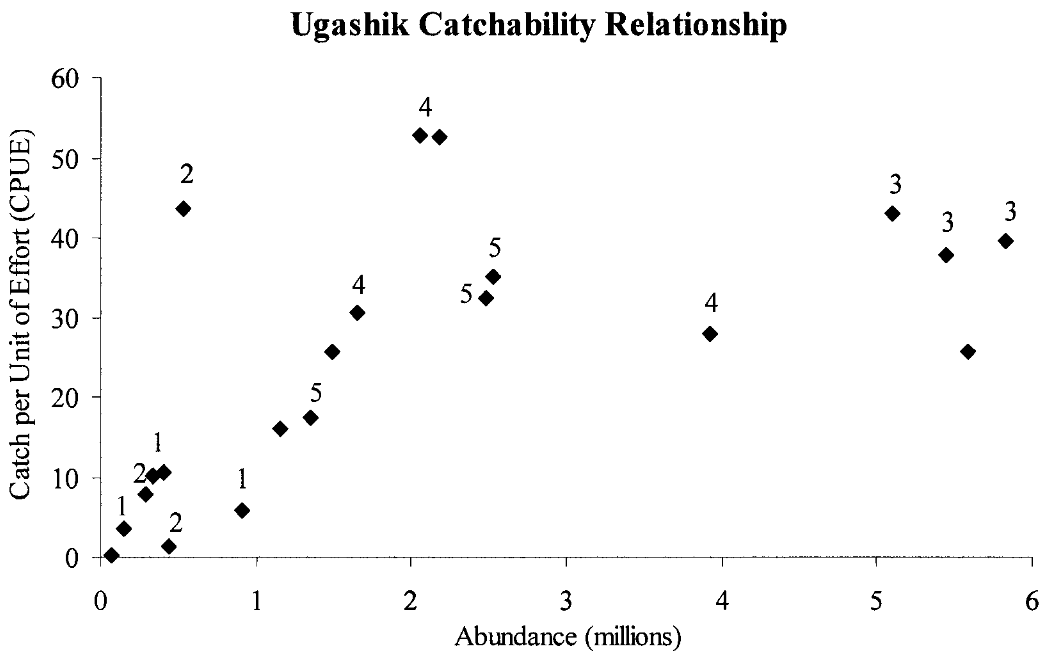


Figure 2.7. Relationship between observed catch per unit of effort (CPUE) and true abundance in millions over the time series. Values 1 through 5 indicate the particular three-year abundance combination (see Tables 2.1 and 2.3).

Table 2.1: Robustness simulation setup. Levels of measurement error in percent CV are shown for the escapement index and abundance data. The two datasets make a total of 20 pairs to be simulated (pair 0,0 (escapement index CV, sonar CV) does not contain error, only the five three-year combinations were necessary for this pair). Random variables (r_y and v_t for escapement and abundance data respectively) are the same 100 sets for each measurement error level. The same five sequences of abundance subsets were also used in every random variable set except the initial abundance combinations, where all possible combinations of one, two and three variables were simulated. The bolded number by the abundance year subsets indicates the number designation for good versus poor combination scenarios.

Dataset	Measurement Error CV (%)	Random Variables (r_y, v_t)	Abundance Subsets (years)
Initial Abundance	0	0	All possible combinations (1,561)
			(1) 1968, 1969, 1970
Escapement Index	Five Levels: 0, 10, 25, 50, 80		**(2)** 1975, 1976, 1977
		100	**(3)** 1994, 1995, 1996
Abundance	Three Levels: 0, 5, 10, 25		**(4)** 1997, 1998, 1999
			(5) 2001, 2002, 2003

Table 2.2: Performance measures of abundance and escapement estimates from initial all possible combinations of abundance years.

Combinations	Abundance		Escapement	
# of Years	Bias	Precision	Bias	Precision
1	24.5	37.0	50.8	54.4
2	17.1	32.8	35.1	48.1
3	13.7	30.5	28.0	44.7

Table 2.3: Measurement error pair performance measures by good (scenarios 2, 4, and 5) and poor (scenarios 1 and 3) combinations for all abundance and escapement estimates. S is the abundance measurement error percent coefficient of variation (CV) and E is the escapement measurement error percent CV. Combo is the abundance subset of three years.

	Combo		2 (1975, 1976, 1977)				4 (1997, 1998, 1999)				5 (2001, 2002, 2003)			
	S	E	Abundance		Escapement		Abundance		Escapement		Abundance		Escapement	
			Bias	Precision	Bias	Precision	Bias	Precision	Bias	Precision	Bias	Precision	Bias	Precision
Good Combinations	0	0	3.8	17.2	8.9	27.4	11.3	30.7	21.6	45.1	4.9	27.9	8.3	41.8
	5	0	3.5	17.2	8.2	27.3	11.6	30.8	22.1	45.3	5.2	28.1	9.0	42.1
	10	0	3.3	17.3	7.7	27.3	11.9	31.0	22.9	45.7	5.7	28.4	10.0	42.6
	25	0	3.0	18.3	6.8	28.4	13.9	32.4	27.0	48.1	8.0	30.0	15.0	45.9
	0	10	3.8	17.7	8.7	28.9	11.3	31.2	21.3	46.4	5.1	28.5	8.4	43.3
	5	10	3.5	17.6	8.0	28.8	11.5	31.3	21.9	46.6	5.2	28.7	8.7	43.4
	10	10	3.2	17.7	7.4	28.8	11.9	31.6	22.7	47.0	5.6	28.9	9.7	43.9
	25	10	2.9	18.7	6.5	29.8	13.9	32.9	26.9	49.5	7.5	30.4	14.0	46.9
	0	25	3.6	20.0	7.9	35.8	11.4	33.9	21.1	52.7	5.2	31.3	8.1	49.2
	5	25	3.2	19.8	6.9	35.4	12.2	34.2	22.5	53.2	5.6	31.4	9.0	49.3
	10	25	2.8	20.1	6.0	35.5	11.7	34.1	21.8	53.0	6.1	31.6	10.2	49.7
	25	25	2.6	20.9	5.4	36.2	13.0	35.3	24.7	55.4	8.5	33.2	15.3	53.0
	0	50	3.6	26.8	6.0	51.6	13.0	41.0	22.8	67.5	6.6	38.3	9.1	63.3
	5	50	2.7	26.3	4.2	50.4	14.5	42.0	25.3	69.4	7.9	38.5	11.8	64.1
	10	50	2.3	26.1	3.2	50.0	15.0	42.2	26.4	69.7	9.0	39.3	13.7	65.5
	25	50	2.0	26.5	2.3	50.0	17.9	44.6	32.8	73.6	11.6	41.0	19.7	68.4
	0	80	1.6	31.1	-0.2	61.7	15.8	49.4	25.5	83.9	9.3	45.0	12.0	76.8
	5	80	1.1	30.7	-1.1	60.6	15.9	49.2	26.0	83.6	8.8	44.8	11.6	76.4
	10	80	1.3	30.9	-0.7	61.0	17.1	50.1	28.4	85.3	10.4	45.9	14.4	78.3
	25	80	1.0	30.8	-1.5	60.2	21.1	53.3	36.6	90.5	12.4	47.7	19.0	81.4

Table 2.3: Continued

	Combo		1 (1968, 1969, 1970)				3 (1994, 1995, 1996)			
	S	E	Abundance		Escapement		Abundance		Escapement	
			Bias	Precision	Bias	Precision	Bias	Precision	Bias	Precision
Poor Combinations	0	0	39.5	43.7	86.6	66.5	28.2	39.0	57.5	57.4
	5	0	39.4	43.7	86.2	66.4	28.9	39.3	59.0	57.9
	10	0	39.3	43.7	86.2	66.5	30.2	40.0	61.9	59.0
	25	0	40.2	44.4	88.0	67.6	37.2	43.9	77.5	65.7
	0	10	38.7	43.7	84.7	67.4	27.9	39.4	56.6	58.8
	5	10	38.5	43.6	84.3	67.3	28.6	39.8	58.1	59.5
	10	10	38.5	43.7	84.3	67.3	29.9	40.6	61.1	60.7
	25	10	39.7	44.6	86.8	68.9	36.6	44.5	76.0	67.2
	0	25	35.7	44.4	77.4	71.8	25.5	41.5	50.8	65.0
	5	25	35.5	44.4	77.1	71.7	25.9	41.7	51.7	65.3
	10	25	35.5	44.4	77.1	71.8	27.2	42.5	54.7	66.5
	25	25	37.1	45.7	80.6	74.1	33.1	46.3	67.9	72.7
	0	50	28.7	47.0	60.4	81.6	19.8	45.0	37.3	75.5
	5	50	28.7	47.0	60.8	81.7	21.3	46.0	40.5	77.3
	10	50	29.0	47.0	61.2	81.9	23.5	47.5	45.2	79.6
	25	50	29.9	47.9	63.2	83.4	36.4	56.4	72.8	93.8
	0	80	22.4	50.2	44.5	90.3	14.0	47.4	24.1	82.9
	5	80	22.3	50.1	44.3	90.1	15.1	48.6	26.3	84.6
	10	80	22.4	50.1	44.5	90.2	18.2	50.3	32.4	87.6
	25	80	23.4	51.1	46.8	91.9	30.3	59.5	57.9	102.1

3 Accounting for Climate Variability in Forecasting Pacific Salmon in Data-Limited Situations [3]

3.1 Abstract

Poor understanding of the major sources of environmental influence on Pacific salmon precludes quantitative forecasting in data-limited situations. Since 1997, low numbers of chum salmon returning to the Kuskokwim and Yukon Rivers of Alaska have resulted in low harvests and significant negative economic and social impacts to rural residents of the region. The causes of these recent declines are unclear; however, poor ocean conditions for survival are thought to be important. No formal forecast has been available for this region, as estimates of the population size necessary to derive a quantitative forecast of returns were lacking. We recently generated abundance and escapement estimates for these two river systems. Our objectives in this study were to describe the spawner-recruit dynamics of this system and to identify important environment-recruit relationships.

We explored a set of variables with plausible mechanistic relationships to five biological processes: freshwater survival, early marine survival, early marine predation, open-ocean survival, and open-ocean competition. We winnowed variables in these life history categories through an exploratory phase, and then used formal model selection procedures on those remaining variables under restricted combination scenarios. Our best

[3] Authors: S. Kalei Shotwell, Milo D. Adkison, and Dana H. Hanselman. Journal: Proceedings of the 21st annual Lowell Wakefield Fisheries Symposium: Assessment and Management of New and Developed Fisheries in Data-Limited Situations, October 22-23, 2003. Currently in review for publication.

models implied strong environmental effects and explained 89% and 81% of the variability in the data in the Kuskokwim and Yukon respectively. Cross validation estimates of forecast error were much smaller for models containing environmental covariates, confirming their utility. We also performed stepwise variable selection on the same set of reduced predictor variables. Results were similar to the previous models, yet identified the most influential life history stage rather than the broad scope of the restricted category-based models. We recommend managers use both forms of model selection and concentrate future research efforts on processes that confirm the mechanisms implied by the best predictor variables. We caution managers to be conservative when applying these models to management decisions and to consider simulation analyses to incorporate uncertainty in the reported estimates. The procedures developed here are applicable to other data-limited salmon systems.

3.2 Introduction

Fisheries management is often hindered by sparse data. These data-limited situations are typical of new and developing fisheries where the practical constraints of a large geographic management area or a small local economy limit data collection. Managers are responsible for developing appropriate regulations for fisheries, even when conventional estimates of stock and recruitment are poor or unavailable. A typical approach is to produce qualitative assessments in the form of harvest outlooks or informal run projections. Unfortunately, these measures are limited in scope and predictive capability. To produce a reliable quantitative forecast for a given region, it is necessary to have some measure of stock productivity and a forecasting procedure suited to the system's conditions (Haddon 2001, Chatfield 1984).

Management of chum salmon of the Kuskokwim and Yukon Rivers (Figure 3.1) provides two examples of such data-limited situations. Chum salmon (*Oncorhynchus keta*) of these systems support important subsistence and commercial fisheries for rural area residents. Currently, however, there are no rigorous quantitative procedures for forecasting and managing chum salmon of these rivers because historic estimates of escapement (spawner abundance) and total run size have been considered unreliable or inadequate for developing such procedures (Burkey et al. 2002, Bergstrom et al. 2001). Instead, the Alaska Department of Fish and Game (ADFG) produces informal run outlooks for these rivers based on available escapement estimates, age composition, recent abundance trends, and anticipated harvest given current management regulations (Eggers 2002). The fisheries are managed inseason based on assessments from subsistence reports, test-fish catches, commercial catch statistics, main stem sonar, and tributary escapement projects such as aerial surveys, counting towers, weirs, and tributary sonar counts (Eggers 2002). The primary management objective for chum salmon in the Kuskokwim and Yukon Rivers is to ensure adequate spawning escapements (JTC 2002), which are typically set in accordance with historical escapement levels (Burkey et al. 2002). Recently escapement goals were developed for two early-run chum salmon stocks in the Yukon River basin based on spawner-recruit relationships; however, these analyses rely on broad assumptions about stock composition in the commercial harvest (Clark and Sandone 2001).

There have been severely decreased harvests of chum salmon in the Kuskokwim and Yukon Rivers since 1997. The average annual chum salmon harvest recently dropped from 2 million fish (1980-1996) to 0.3 million (1997 to 2001), and was generally coupled with low chum salmon escapements. Recent declines prompted the governor to issue formal declarations of economic disaster for this region. The low harvests coupled with declines in market value of chum salmon (Buklis 1999; Eggers 2002) have resulted in significant negative social and economic impacts in many rural communities along the Kuskokwim and Yukon Rivers.

Poor ocean conditions for salmon survival are among the list of plausible causes for the recent declines in Kuskokwim and Yukon River chum salmon (Geiger and Hart 1999). The declines were observed across widely separated river systems, indicating poor conditions affecting fish that share a common marine environment (Kruse 1998). In addition, oceanic conditions in the eastern Bering Sea since 1997 have been highly variable beginning with fluctuations in the physical environment as warm sea surface temperature (SST) anomalies occurred in conjunction with the 1997/98 unusually intense and early El Niño event (Niebauer 1999, Stabeno and Hunt 2002). Unusually weak winds, anomalous mixing events, and rapid melting of the ice edge led to observations of aquamarine waters extending as far south as Bristol Bay and into the Chukchi Sea in 1997/98. Such chalky-type waters often indicate a predominance of coccolithophores in the phytoplankton bloom. These events persisted through 2001 and reappeared again in 2003, suggesting relatively nutrient-deficient oceanic conditions (Stabeno and Hunt 2002). The phytoplankton biomass in the Bering Sea is typically dominated by diatoms and the persistence of a large coccolith bloom implies a reorganization of the food web and potentially more steps to transfer energy through this system (Olsen and Strom 2002). These extreme and persistent conditions in the Bering Sea were associated with unprecedented changes throughout the ecosystem, including declines of zooplankton, salmon, northern fur seals, Steller sea lions and seabirds and substantial increases of jellyfish and baleen whales (Stabeno and Hunt 2002).

Our study objective was to develop rigorous, mechanistically-based models to improve forecasts of Kuskokwim and Yukon River chum salmon and to better understand the potential effects of environmental conditions on their survival and recent declines. As a first step, Shotwell and Adkison (*in press*) proposed a new methodology for deriving estimates of total escapement and run size of summer chum salmon in each of these data-limited systems. In this paper, we develop stock-recruitment models that combine those abundance estimates with environmental variables that may be useful predictors of recruitment.

Because the time series of available stock-recruitment data for Kuskokwim and Yukon River chum salmon are short (roughly 20 years in each case), and because numerous candidate environmental variables were considered (over 30 in each case), we undertook a three-stage approach designed to maintain biological realism and reduce the chance of spurious relationships. In data-limited situations, it is well known that putative environment-recruitment relationships often break down as new data become available (e.g., Myers 1998). This is more likely to occur when investigating environmental indices that poorly reflect the temporal and/or spatial scales of biologically reasonable relationships. For example, analyses of spatial covariation in survival rates of salmon suggest that important environmental effects occur primarily at local or regional scales (e.g., Pyper et al. 2002). Thus, in our first stage of model development, we attempted to select environmental variables with temporal and spatial scales consistent with their potential effects (either direct or indirect) on recruitment. We then organized the variables into five categories related to the timing and nature of those potential effects by life history mechanism (freshwater survival, early marine survival, early marine predation, open-ocean survival, and open-ocean competition), and only considered one or two variables from a given category in each alternative model. For each biological mechanism, we selected environmental factors from appropriate locations and time periods, given our understanding of chum salmon life history.

In the second stage, we conducted an exploratory analysis to limit the number of candidate variables to those that exhibit at least some relationship with the residuals of the basic spawner-recruit model. We used a conservative correlation measure to eliminate variables and inspected cross-correlations between variables to eliminate redundancy within a given biological category. Models were then developed based on the remaining variables and evaluated using a formal model-selection criterion to further limit the set of models to a relatively small group. Following this we used regression diagnostics and prediction error to inspect competing models for predictive ability and potential violation of assumptions. We also examined the biological realism of the models by analyzing the magnitude and direction of parameter coefficients across alternative models. We then produced forecasts for the best model with estimates of forecasting error and compared these results with those of the base model that did not include environmental predictors. Our approach to model development and selection should produce a more accurate and reliable forecast than model selection without the life history categories and identify indicators of chum salmon variability for future management decisions in these data-limited systems.

3.3 Methods

3.3.1 Salmon Data

Chum salmon have one of the broadest ocean distributions of any Pacific salmon species, ranging in Asia from Korea to the Laptev Sea in the Arctic Ocean and in North America from California to the Mackenzie River in the Beaufort Sea (Salo 1991). In addition, some populations of Yukon River chum salmon travel more than 2,000 miles upriver to spawn. A given river system often has two genetically distinct groups of chum salmon that differ in their run timing (early and late, Salo 1991). In this study, we concentrate on the early runs of chum salmon to the Kuskokwim and Yukon Rivers. The early run population of chum salmon begins to enter the Kuskokwim River from the ocean in early June, with numbers peaking in early July and diminishing through early August (Molyneaux 1998). In the Yukon River, the early run population (referred to as "summer chum") enters freshwater beginning in mid-June, peaks in late June to early July, and diminishes through late July (T. Lingnau and D. Molyneaux, Alaska Dept. of Fish and Game, personal communication).

Following emergence, chum salmon immediately begin their seaward migration, beginning in April to May in the Kuskokwim and Yukon Rivers (D. Molyneaux, Alaska Dept. of Fish and Game, personal communication). Chum fry typically feed on larval and adult insects during their early life history but it is unknown to what extend they feed during downstream migration in the Kuskokwim and Yukon Rivers. Often major predators of chum salmon during the early life stages are coho salmon (*Oncorhynchus kisutch*), cottids and trout (Healey 1982, Salo 1991). However, there is no information on predation mortality for summer chum along the Kuskokwim and Yukon Rivers (C. Zimmerman, U.S. Geological Survey, personal communication). The early marine distribution of chum salmon is also relatively unknown; however, chum juveniles originating from the Kuskokwim and Yukon are thought to move out of the Bering Sea to the North Pacific by late fall or winter. They typically spend the next few years feeding primarily on gelatinous zooplankton (e.g., pteropods, appendicularians, jellyfish) and crustaceans (e.g., eupahusiids, copepods, amphipods) in the Gulf of Alaska (Tadokoro et al. 1996) and return primarily in June of their maturing year through the central Aleutian passes (Salo 1991). Chum salmon mature after two to six years of age, with four- and five-year olds dominating in the Kuskokwim and Yukon Rivers (D. Molyneaux, Alaska Dept. of Fish and Game, personal communication).

We used annual estimates of escapement and total abundance for the Kuskokwim (1976-2000) and Yukon Rivers (1975-1999) from Shotwell and Adkison (*in press*) and were able to update the Kuskokwim values through 2002. We used percent-at-age data for each river to derive estimates of recruitment by brood year (i.e. the abundance of recruits corresponding to a given brood-year escapement). For the Kuskokwim River, numbers-at-age data were available from samples taken in the commercial fishery from 1976-1979, 1981-1992, 1994-1996, and 1998. This data was weighted by the commercial catch at the time the sample was taken and expressed as percent-at-age. For the remaining years we used percent-at-age estimates from available projects throughout the river. Specifically, we used data from the Aniak River sonar for 1980 and 1997-1999, the Tuluksak River weir for 1993, and the Bethel Test Fishery for 2000-2002 (D. Molyneaux, Alaska Dept. of Fish and Game, personal communication).

For the Yukon River, we obtained age data from the ADFG Mark, Tag and Age Laboratory. We used test fishery 5½-inch mesh samples (Flat Island test fishery from 1975-1978, Big Eddy test fishery from 1979-1983 and 1986-1999, and Middle mouth test fishery for 1985) with the exception of one year, 1984, where we used Big Eddy 8½-inch mesh samples of chum because no other age samples were available for that year. Age composition is thought to change throughout the duration of the run in any given year (D. Molyneaux, Alaska Dept. of Fish and Game, personal communication). However, due to limited data, samples were pooled across the season in order to compute the age proportions for a given year. We consider ages three, four, five and six for both rivers over all years.

Recruits by brood year were then calculated by first multiplying the percent-at-age by the abundance for a given year and then offsetting the recruits for that brood year by the age. Total recruits were then just the sum of the individual ages for a given brood year (Quinn and Deriso 1999). Since six-year olds constitute on average just 0.01% and

2.0% of the total population for the Kuskokwim and Yukon Rivers respectively, we included a final year where returns were only available through age five. This resulted in spawner-recruit data by brood year from 1976 to 1997 for the Kuskokwim River and 1975 to 1994 for the Yukon River.

3.3.2 Environmental Data:

We selected environmental variables for each river that reflected conditions during the life history stages potentially most influential on summer chum salmon survival (Table 3.1). Variables that pertain to the freshwater stage were generally lagged one year from spawning to represent conditions during emergence or outmigration. Early marine residence variables were lagged one to two years from spawning to represent the general state of the Bering Sea during entry or after one year of ocean residence. We defined open-ocean competition as occurring between 2-4 years after spawning, during the period of co-residence with the major populations of Japanese chum and pink salmon (*Oncorhynchus gorbuscha*). Where appropriate, variables were averaged over the months considered (Table 3.1) and then all variables were standardized by their respective mean and standard deviation.

3.3.3 Model Development

We used the linear form of the generalized Ricker stock-recruitment curve as our model for estimating survival rates (R/S) of summer chum:

(1) $$\ln(R/S) = \ln(\alpha) - \beta S + \gamma_1 X_1 + \ldots + \gamma_p X_p + \varepsilon, \quad \varepsilon_y \sim N(0, \sigma_\varepsilon^2).$$

Here R is recruits, S is spawners, $\hat{\alpha}$ is the productivity parameter that determines recruits per spawner at low stock levels, and $\hat{\beta}$ is the density-dependent parameter or the decrease in survival rate as S increases, $X_1 \ldots X_p$ are the environmental predictor variables for a given model and $\hat{\gamma}_1 \ldots \hat{\gamma}_p$ are the associated scaling parameters (Quinn and Deriso 1999, Haddon 2001). Recruits-per-spawner is generally assumed to have lognormal error; therefore, we express $\ln\left(\hat{R}/S\right)$ with normal random error ε_y having a mean zero and standard deviation σ_ε (Hilborn and Walters 1992). As our base model, we used the simple linear Ricker model; i.e., the model above without any environmental predictors.

Initially, we collected a total of thirty-four and thirty-six potential variables for the Kuskokwim and Yukon Rivers, respectively. This is a fairly extensive set to consider for model selection (Burnham and Anderson 1998). We therefore conducted an initial exploratory analysis to limit the number of candidate variables then used a formal model selection criterion to arrive at our final best model(s) for each river system.

3.3.3.1 Exploratory phase

We calculated Pearson product moment correlations (r-value) between each of the predictor variables and the estimated residuals from our base model. We then ran a simple F-test on these correlation values to determine which variables were significantly correlated with the spawner-recruit data (Kleinbaum et al. 1998). We used a conservative reduction approach, limiting the potential variables to those with r-values of at least 0.2, which approximately corresponded to p-values of 0.35. This served to eliminate variables that would add very little to explaining the variability in the data and still retain at least some variables from each life history category. Following this exploratory phase we examined cross-correlations among environmental variables to check for redundancy within a particular life history category.

3.3.3.2 Selection phase: Category-based models

Using a combination of AD Model Builder (version 5.01, Otter Research) and S-PLUS software (version 6, release 2, Copyright 1988-2001 Insightful Corp.), we examined a family of models based on the remaining variables from the exploratory phase. We allowed models with up to five variables and included all nested models (i.e. models with fewer than five variables). The initial five variable models were created from one of two scenarios. First, we examined all possible combinations in which one variable was selected from each of the five life history categories (Table 3.1). Second, we created models where we allowed two variables from the early marine residence category and three additional variables with only one variable selected from each of the remaining four categories. We explored the second option because Pyper et al. (2002) suggested that the early marine phase might be the most important in determining survival. We compared models fits using the Akaike Information Criteria (AIC_c) for small sample size (Burnham and Anderson 1998):

(3) $$AIC_c = n\ln(\hat{\sigma}^2) + 2K\left(\frac{n}{n-K-1}\right)$$

(4) where, $\hat{\sigma}^2 = \frac{\sum \hat{\varepsilon}_i^2}{n}$, (the MLE of σ^2)

where n is the number of observations, K is the number of parameters, and $\hat{\varepsilon}_i$ are the estimated residuals for a particular candidate model (Burnham and Anderson 1998). For each candidate model there were at least three parameters, $\hat{\alpha}$, $\hat{\beta}$, and $\hat{\sigma}$, plus $\hat{\gamma}_1 ... \hat{\gamma}_p$, depending on the model. We computed the differences (Δ_i) between the lowest AIC_c value and the AIC_c values of all other candidate models in the set. Our "best" or preferred model was the model with the lowest AIC_c. However, a model for which the Δ_i was small ($\Delta_i < 3$) has substantial support and can be considered to fit the data almost equally well (Burnham and Anderson 1998, Mueter et al. 2002a). Therefore, we present all models that were selected as plausible ($\Delta_i < 3$) with their respective parameter estimates and predictor variables.

3.3.4 Model Diagnostics and Cross-validation

Following model selection, we assessed the consistency and reliability of the plausible models through regression diagnostics and estimates of prediction error. We checked all parameter coefficients for statistical significance and for large changes in magnitude between models as this is an indicator of a potential spurious relationship. We examined the sign of each parameter to determine if it made biological sense and inspected diagnostic plots of the residuals for the presence of non-normality, outliers, and autocorrelation. We then calculated the multiple r-squared (R^2) value of all models and several sub-models to determine the relative contribution of key variables to the improvement in fit.

We calculated estimates of forecast error (CVFE) for the equally plausible models by cross-validation (Efron and Tibshirani, 1993; Adkison and Peterman 1999):

$$(5) \qquad CVFE = \sqrt{\frac{\sum_{i=1}^{n}(y_n - y_{n-i})}{n}}.$$

Here y_n is the sum of squared residuals over all years (n) and y_{n-i} is the sum of squared residual over all years minus the squared residuals of the left out year (i). We calculated CVFE values (Equation 5) for each of the competing models and generated 80% confidence intervals (CIs) around the estimate of recruits for each model (Adkison and Peterman 1999). We reserved the final year of each dataset to allow comparison of the actual observation for this final year with the forecasted value. We compared models for consistency in CVFE and whether the real value for the final observed year fell within the 80% CIs for each model. We then constructed new estimates of CVFE using all the data and generated forecasts one year into the future for summer chum returns in both the Kuskokwim and Yukon Rivers. We present yearly forecasts with 80% CIs for the best model and the base model.

3.3.5 Influence of Biological Categories: Stepwise Models

Our restricted scenarios that constrained all possible models to selecting one or two (early marine residence only) variables from each of the life history categories potentially mask other models with higher explanatory power. We developed the scenarios to reduce the total number of models examined following the exploratory phase. This method also limits the potential for spurious relationships arising from the interaction between variables and pinpoints the most influential variables within each category. It may be that one category is completely dominant and explains more variability than several different categories. We investigate this possibility through stepwise variable selection where variables incorporated into the model are reexamined at every addition or deletion (step) of another candidate variable (Kleinbaum et al. 1998). Again we used S-PLUS software (version 6, release 2, Copyright 1988-2001 Insightful Corp.) to apply the step function to the set of variables for each river following the exploratory phase. The process begins with the base model and then performs single variable additions and deletions based on the Akaike Information Criteria (*AIC*) statistic (Burnham and Anderson 1998). If the *AIC* value is lower than the current model, a variable is added or deleted. We report the variables selected and mulitple R^2 value for the "best" step model and compare results with that of the category-based model selection.

3.4 Results

Initial plots of the observed data suggest a strong stock-recruitment relationship for the Kuskokwim and more of a shotgun pattern for the Yukon (Figures 3.2a & 3.2b). The exploratory phase of our model selection eliminated ten variables from the Kuskokwim model and fifteen variables from the Yukon model (Table 3.1). This left 6, 9, 2, 4, 4 variables in the Kuskokwim and 6, 7, 1, 4, 3 variables in the Yukon for the freshwater, early marine residence, early marine predators, open-ocean, and open-ocean competition categories, respectively. The second phase of model selection drew different models from these twenty-five and twenty-one remaining variables.

The cross-correlation matrix of the variables following the exploratory phase did exhibit some high r-values ($0.5 \leq r \leq -0.5$) within a given life history category. In general, high correlations existed between successive lags of a particular variable namely Asian chum salmon (ACS, ACD, ACR) and coho predators (WAKCF, WAKCJ). Other high correlations occurred between variables in the freshwater and early marine residence categories. This was found between spring-time air temperature (ATPF) and streamflow or Yukon Delta Iceout (STPF, STSR, IYDA) and between ocean sea ice cover (ICF, ICS) and winter surface air temperature, strong winds, or sea surface temperature (SATF, SATS, SWMF, SWMS, MSSTF). In the Yukon, there was also a high correlation between winter surface air temperature (SATF) and sea surface temperature (MSSTF) as well as between Asian chum salmon (ACD) and Asian pink salmon (APS). These high correlations indicate some redundancy between predictor variables; however, we choose to retain all variables following the exploratory phase. We did this because the most appropriate lag for determining survival in summer chum salmon is unknown. Also mechanisms driving more complex variables such as ocean sea ice cover invariably originate from interactions between simpler physical variables such as air temperature or winds. We expect these somewhat "nested" variables to be highly correlated but again it is unknown which is best for explaining changes in survival.

The set of all plausible category-based models (AIC_c results where $\Delta_i < 3$) are presented in Table 3.2 for both rivers along with predictor variables in each model. For comparison, we also report the base model with no environmental predictors. There were eleven equally plausible models for the Kuskokwim and four models for the Yukon.

Twelve and six different predictor variables were contained in the set of plausible models for the Kuskokwim and Yukon, respectively (Table 3.2). The "best" AIC_c-selected model was a three-parameter model for both rivers (Table 3.2). Predictor variables for the Kuskokwim were the spring Bethel air temperature during the freshwater stage (ATPF), the spring along-peninsula component of wind stress during early marine residence (WUPSF), and the number of Kuskokwim adult coho salmon as early-marine predators (WAKCF). The three variables for the Yukon were the spring precipitation at Tanana station during the freshwater stage (PRPF), the late-spring/summer strong winds at M2 station in the eastern Bering Sea during early marine residence (SWMF), and the summer Arctic Oscillation lagged one year in the open-ocean stage (AOSF).

3.4.1 Model Diagnostics and Cross-Validation

We present parameter estimates for the equally plausible category-based models and sub-models for both rivers along with their respective standard errors and significance values (Table 3.3). All parameter coefficients were consistent in direction across models for a given river, as were the coefficients for variables shared among rivers. There were no significant outliers or trends in the residuals of the plausible models in either river. We discuss possible trends in the predictor variables, differences in the magnitude of parameters, biological realism of parameter values, deviations from assumptions about the distribution of residuals, and autocorrelation in residuals for each river separately.

3.4.1.1 Kuskokwim Model

There was significant autocorrelation in the spawner and Japanese chum (ACS) data (Table 3.4). Weak but not significant autocorrelation also existed in the log recruits per spawner ($\ln(R/S)$), coho predators (WAKCF), winter and summer Arctic Oscillation (AOWF and AOSF) data. The same three variables were included in every plausible model: spring air temperatures (ATPF), spring wind stress (WUPSF), and coho predators (WAKCF). The parameter estimates for these variables were significant in all models but additional parameters estimates (models 2 through 11) were not significant. Biologically implausible signs on parameter values were estimated for the winter wind stress in the first year (WUPWF) and summer wind stress in the second year (WUPSS), which appear in models 8, 9, and 11 (Table 3.1, Table 3.3). The base model and models 3, 8, and 11 exhibited slight deviations from normality in their residuals. Slight to significant negative autocorrelation existed in all models at lag 5, with the exception of the base model with slight positive autocorrelation at lag 2 (Table 3.4). After inspecting Cook's distance plots of residuals, the base model and models 1, 4, 8, and 11 fit the most recent years relatively well and other models fit earlier years better.

The relative contribution of each model to the improvement in fit from the base model is shown by the absolute increase in R^2 between the competing eleven models and the base model (Table 3.5). It is clear from the base model R^2 that the basic spawner-recruit model is fairly informative, explaining 54% of the variability in the data. On average, the percent increase in variance explained by the eleven competing models was

36% from the base model, regardless of the number of parameters. Also, the percent increase in R^2 for the four- and five-parameter models was only 1% to 3% from the best AIC_c three-parameter model (model 1). Sub-models of the best AIC_c selected model identified the relative contribution of the three key variables, spring air temperatures (ATPF), spring wind stress (WUPSF), and coho predators (WAKCF) (Table 3.5, Kuskokwim models 12-17). Variables WAKCF and ATPF seem to contribute the most alone. Also, residual plots of the sub-models showed that any two-parameter combination of these three key variables explained the most recent years relatively well. The CVFE across models was very consistent with the exception of the base model, for which CVFE was much larger (Table 3.6). The actual observation for 1997 recruits fell within the CI's for the base model and competing models 1, 3, 4, 8, and 11.

Model 1 was the best or preferred model because it had the lowest AIC_c. This model was also the most parsimonious model, had no trends in residuals or deviations from assumptions, had significant, consistent and biologically reasonable parameter estimates, and fit the most recent years moderately well. Figures 3.3a & 3.3b show yearly forecasts from 1976 to 1996 and include the 1997 forecast in both the best and base model. For the most part, CI's are substantially smaller in the best model versus the base model. We did not, however, include the 1998 forecast in the best model plot (Figure 3.3b) because the estimate was well above the previous predicted and observed abundances. We discuss likely reasons for the anomalous 1998 estimate below.

3.4.1.2 Yukon Model

Significant autocorrelation existed only in the Japanese chum and pink (ACS and APS) data, while weak but not significant autocorrelation existed in the strong winds (SWMF) data (Table 3.4). For the competing Yukon models, two variables were selected in all models except the base model: spring precipitation (PRPF) and summer Arctic Oscillation (AOSF). Two other parameters were also selected more than once in the competing models: strong winds (SWMF) and Japanese chum lagged two years (ACS). Parameters of the first three variables were significant in all models, while ACS was not significant in either model, but very close in one model at 0.056 (Table 3.3, Model 3). An implausible sign for a parameter estimate existed only for Japanese pink (APS) in model 4 (Table1, Table 3.3). The base model and model 4 exhibited slight deviations from normality and the residual-fit (r-f) plot of the base model showed a much greater spread in the residuals than the fitted data. There was only slight (not significant) negative autocorrelation in the residuals of models 2 and 4 at a lag of 5 (Table 3.4). Plots of Cook's distance demonstrated that all models including environmental parameters explained the most recent years fairly well.

The base model was uninformative, explaining only 6% of the variability in the data (Table 3.5). Percent increase in variance explained by the four competing models was substantial at 77% from the base model regardless of the number of parameters. The percent increase for the four parameter models was only 2% to 3.5% relative to the best AIC_c three-parameter model (model 1). We generated several sub-models of the variables chosen most often in the AIC_c selection process: spring precipitation (PRPF), summer

Arctic Oscillation (AOSF), strong winds (SWMF), and Japanese chum (ACS) (Table 3.5, Yukon models 5-17). The summer Arctic Oscillation (AOSF) and Japanese chum (ACS) variables explain the most variability alone at 28% and 34%, respectively. Summer Arctic Oscillation (AOSF) and spring precipitation (PRPF) together explained 62% more variability than the base model. The best AIC_c model (model 1) had a percent increase from the base of 75%. Values of CVFE were very consistent across all plausible models, while that of the base model was nearly twice as large (Table 3.6). The actual observation for 1994 recruits fell within the CI's for only model 2, but was very close to the lower bound for models 1 and 3.

Model 1 was the best model because it had the lowest AIC_c. Again, this model was also the most parsimonious, had no trends in residuals or deviations from assumptions, had significant, consistent and biologically reasonable parameter estimates, and fit the most recent years very well. Figures 3.4a & 3.4b illustrate the improvement in forecast error between the base and best models from 1975 to 1993 with the 1994 and 1995 predictions.

3.4.2 Influence of Biological Categories: Stepwise Models

The "best" selected model from the stepwise procedure was a three-parameter model for both rivers. Parameter estimates for both $\hat{\alpha}$ and $\hat{\beta}$ were similar to that reported for the category-based models. However, only two variables were chosen that were from the list of equally plausible models presented in Table 3.2. For the Kuskokwim step model, the best predictor variables were strong winds in the early marine residence

(SWMS, model 7, Table 3.3), Asian chum salmon in the second year (ACS, model 12, Table 3.3), and Asian chum salmon in the third year (ACD). Parameter estimates for SWMS and ACS were similar to that reported in the category-based models. The R^2 value was slightly lower than the best category-based model at 0.877. In the Yukon, two predictor variables were also chosen in the category-based best model, spring precipitation in freshwater (PRPF) and summer Arctic Oscillation in the open-ocean (AOSF). The third variable was streamflow at Tanana station in freshwater (STSR). Parameter estimates for the PRPF and AOSF were similar to the category-based model. The R^2 value for this step model was the same as the category-based model at 0.808.

3.5 Discussion

Our structured model-development and selection procedure provided "best" models for the Kuskokwim and Yukon Rivers that explained 89% and 81% of the variability in survival rates, respectively. These are good improvements over the base models, which explained 54% of the variability in the Kuskokwim and only 6% in the Yukon. These increases in explanatory power suggest that adding environmental variables to the stock-recruitment relationships of summer chum salmon in these two river systems may dramatically improve future forecasts of recruitment. Additionally, these models were developed using a process that focused on biologically reasonable links between recruitment and environmental conditions. At a minimum, managers may consider the simple trends in these key variables to formulate some idea of potential fluctuations in returns from year to year. The best predictor variables for each system differed somewhat; however, all seem to show changes in recent years that can account to some extent for the decreased returns to these river systems.

The best category-based predictors for Kuskokwim chum salmon were spring-time air temperature during the freshwater life stage (ATPF), along-peninsula wind stress (WUPSF) during early marine residence, and Kuskokwim coho adult predation (WAKCF) during early marine residence. The relationships between these variables and survival rate were all negative. We expect survival to decrease due to increased predators; however, the other negative relationships may not be obvious. To the extent that air and water temperatures during the freshwater life stage are related, increased temperature may be associated with decreased survival due to increased metabolic rates of salmon fry and decreased dissolved oxygen (Salo 1991). Alternatively, given that monthly air-temperature anomalies are often highly autocorrelated, the time period over which we defined the air temperature index may simply represent a different process that occurred slightly earlier or later in the year. An opposite effect of increasing air temperature is found in the ocean environment. Ocean surface air temperature is typically highly correlated with sea surface temperature, which was found to exhibit a positive relationship with survival rates of Alaska salmon as warm temperatures in the North Pacific Ocean often imply good feeding conditions (Mueter et al. 2002a). We also found a positive correlation between residuals of the base model and several of the temperature-related variables we considered (St. Paul air temperatures (SATF), and Mooring 2 sea surface temperatures (MSSTF), Table1), but these did not show up in the competing models. Therefore, air temperatures will influence survival of chum salmon in altering directions depending on the life history categories. Additionally, fluctuations in freshwater air temperatures are more drastic than ocean air temperatures thereby producing a more direct and stronger influence on chum salmon survival.

Negative values of the along-peninsula wind stress are related to strong winds from the east. These are associated with northward transports through Unimak Pass that are thought to pulse nutrient-rich water from Bering Canyon into the inner front or "green belt" region of the Bering Sea continental shelf (Stabeno and Hunt 2002). We expect a negative relationship with this index and survival as negative values would imply more nutrient rich water transported into the eastern Bering Sea and allow more primary and secondary production. The summer index (WUPSF) has moderate interannual variability but does contain one recent exceptionally positive year, 1998, where anomalous strong west winds forced southward transports through Unimak Pass. This variable may be explaining recent changes in the Bering Sea relatively well as concerns Kuskokwim chum salmon and, therefore, may be an important indicator of survival rates.

The best category-based Yukon predictors were spring-time precipitation in freshwater (PRPF), strong winds at station M2 in the Bering Sea (SWMF), and the summer-time Arctic Oscillation index (AOSF) again all in the first year. The directions of relationships for the first two predictors were positive while the AOSF sign was negative. We expect strong winds to mix new nutrients into the euphotic zone and so produce better feeding conditions for salmon smolts. We may also expect the Arctic Oscillation relationship as positive values are associated with relatively mild, warm conditions and net melting of the Arctic sea ice pack (Rigor et al. 2002), as are the current trends in the

Bering Sea when survival of summer chum salmon was low. We may expect a negative or positive relationship with precipitation and survival rates. High precipitation may mean increased streamflow and more scouring and destruction of redds, therefore decreasing survival. However, precipitation and streamflow indices are only moderately related in our variables and this makes sense in a dry continental climate like the Yukon interior where there is little overall precipitation. In this case, we may expect a positive relationship as more precipitation could imply increased nutrients in the streams through runoff and perhaps more turbid waters that allow predator avoidance.

An important application of the environmental models is that they help explain the lowered survival of the past few years much more than the base spawner-recruit model. Recent trends in the predictor variables suggest warm, mild conditions in the Bering Sea. Freshwater temperatures were warmer (except 1999), anomalous 1998 southward transport, fairly high coho predators (up until 1996, then decreasing to anomalously low 1999 year). Precipitation and wind speeds were lower, and there were large swings in the summer-time Arctic Oscillation. Asian chum salmon show a systematic increase over time, implying increased potential for competition. These indicators all suggest lowered survival rates in these two river systems in recent years.

In conjunction with this, the CVFE for the best models in both systems was much smaller than that of the base model. This is useful to managers as there are tighter bounds about the point estimate implying a better understanding of the stock-recruitment relationship. The prediction for 1995 brood year returns to the Yukon was 1.5 million fish, in line with recent returns. The predicted return for the Kuskokwim was anomalously high. We attribute this to an extremely low return of coho predators that corresponded to an approximate 93% reduction from the average coho harvest over the set of years we considered (1975-2001) and out of the previously observed range of data. Other variables in that year were also indicative of good survival conditions and the spawner biomass was fairly large. This resulted in a very large (and likely unrealistic) prediction, and emphasizes the need for a conservative approach to modeling with environmental predictors under extremely anomalous conditions.

There is some concern for the potential of this modeling procedure to include spurious relationships due to the high number of models evaluated. There were thirty-four and thirty-six initial variables considered for predicting chum salmon survival and the number of permutations of these variables is intractable. We reduced the total number of candidate models by developing restricted scenarios; however, this did not decrease the chance of developing a spurious relationship from any one variable. We, therefore, choose our variables based on ecologically plausible relationships of summer chum salmon survival. The restricted scenarios substantially reduced the possibility of spurious relationships arising from the interaction between variables. We can see the result of no constraints by inspecting the "best" model selected for the Kuskokwim through the stepwise variable selection procedure. Two of the three predictor variables were Asian chum salmon at the two and three year lags. These two variables are highly autocorrelated. Even though this model contains similar explanatory power as the category-based model, it lacks in biological significance since there is high redundancy in the predictor variables. Our restricted scenarios do buffer against this occurrence;

however, we anticipate that the explanatory power of our best model is overstated. Our suggestion is to simulate the environmental model selection procedure to gain a more reliable understanding of explained variability.

We also feel that the stepwise selection procedure may be very informative as a straightforward methodology when variables chosen are biologically meaningful. The best step model for the Yukon where two freshwater variables were chosen (precipitation and streamflow) had equal explanatory power as the best category-based model. In this case, these variables were only moderately positively correlated and may reflect different environmental pressures on chum salmon survival. We suggest exploring both types of methodologies. The category-based procedure explicitly defines major environmental pressures throughout the life history of chum salmon producing a general idea of important predictor variables to monitor. The stepwise procedures will identify the most influential life history stages where future studies could concentrate research efforts.

Finally, it is important to consider the various sources of error in the spawner and recruit indices, the age data, and the environmental data. Often one expects environmental data to be autocorrelated, and in the plausible models evaluated Asian chum salmon, Asian pink salmon, and Kuskokwim spawners exhibited significant autocorrelation. Inflation of significance in parameter estimates occurs when both dependent and independent variables contain significant autocorrelation (Chatfield 1984). However, there was no significant autocorrelation in the dependent variable of log recruits per spawner; therefore, we do not expect a change in the explained variability of the different models with respect to influence of autocorrelation in the independent variables. Autocorrelation in the residuals of a particular model may be explicitly accounted for by including a *p*th order autoregressive term in the parameters (Quinn and Deriso 1999). We found strong negative autocorrelation in the model residuals at a one year lag in all of the competing Kuskokwim models. If one were to suspect this trend to be real, models could include an autocorrelation term such as an ARIMA model to account for this variation. Additionally, the autocorrelation in Kuskokwim spawners may indicate that sibling catches from year to year are another potential variable to consider in this modeling framework. Geiger and Hart (1999) found that last year's catch was fairly useful in predicting summer chum returns for a guideline in the South Peninsula June sockeye fishery.

The estimates of abundance and escapement have inherent error associated with them from the estimation process (Shotwell and Adkison, *in press*). Measurement error in the escapement data may have a large effect on the reliability of these estimates depending on the properties of the whole river sonar information (Chapter 2). The age composition data was fairly difficult to obtain and estimates were made from very heterogeneous data due to limited sampling. These sources of error should be considered when developing biological escapement goals or harvest strategies from these estimates. We report standard errors for the model parameter estimates. However, direct use of these values for productivity and density-dependent parameters can be complicated when calculating management parameters such as optimal stock size and optimal harvest rates (Hilborn and Walters 1992). Annual estimates of precision through mark-recaptures studies, errors in variables approaches, and mixed error models such as the Kalman filter are all potential methods for considering measurement and process error in these models (Hilborn and Walters 1992, Quinn and Deriso 1999). Simulation analyses of measurement and process error that replicate the fishery and environmental conditions of these two river systems should also be conducted to fully understand potential biases in estimating management parameters (Mundy et al. 2001). Managers should use a precautionary approach to these model results and incorporate adaptive management (Mundy et al. 2001) by consistently reevaluating the environmental predictor variables, model selection, and forecasting estimates when new data becomes available.

The environmental variables identified in both the category-based and stepwise models pinpoint key areas for future research. Coho predation was a large predictor of chum salmon survival in the Kuskokwim model and coho have been shown to feed on juvenile chum salmon along their seaward migration (Orsi et al. 2000). Almost nothing is known about the major predators of Kuskokwim and Yukon River summer chum juveniles in the early marine environment (C. Zimmerman, U.S. Geological Survey, personal communication). Investigations that sample regularly in the delta region of both rivers could record timing of ocean entry for smolts and characterize major predators and primary diet. Clearly fluctuations in the freshwater environment are very important in determining summer chum salmon survival, particularly for the Yukon. There is relatively little known about the particular characteristics of the spawning grounds or incubation habitat of summer chum salmon along the Kuskokwim and Yukon Rivers (C. Zimmerman, U.S. Geological Survey, personal communication). Studies concentrating on water quality and food availability throughout index streams or development of remote sensing analysis would be very useful for identifying specific freshwater variables for continued monitoring. Finally other variables might be considered useful for inclusion in these models that are not necessarily life history based. Mundy et al. (2001) suggest the use of all available information to supplement the results of formal modeling approaches such as presented in this paper. The focus of this study was to identify key variables that influence summer chum survival, and to factor these variables into run abundance forecasting models. Our forecasting model may be improved by also considering the influence of interception fisheries, such as the South Peninsula June sockeye fishery (False Pass or Area M).

Given these considerations, we find inclusion of appropriately defined environmental variables to be useful for stock-recruitment analysis and forecasting even in this data-limited situation. There were many environmental indices that we were able to apply to this system. Most of these variables are fairly easy to acquire and are constantly updated. In situations like the Kuskokwim and Yukon rivers, where populations seem to be dwindling for unknown reasons, it is important to be able to generate an understanding of the potential mechanisms involved and to formulate a modeling procedure that accounts for these changes.

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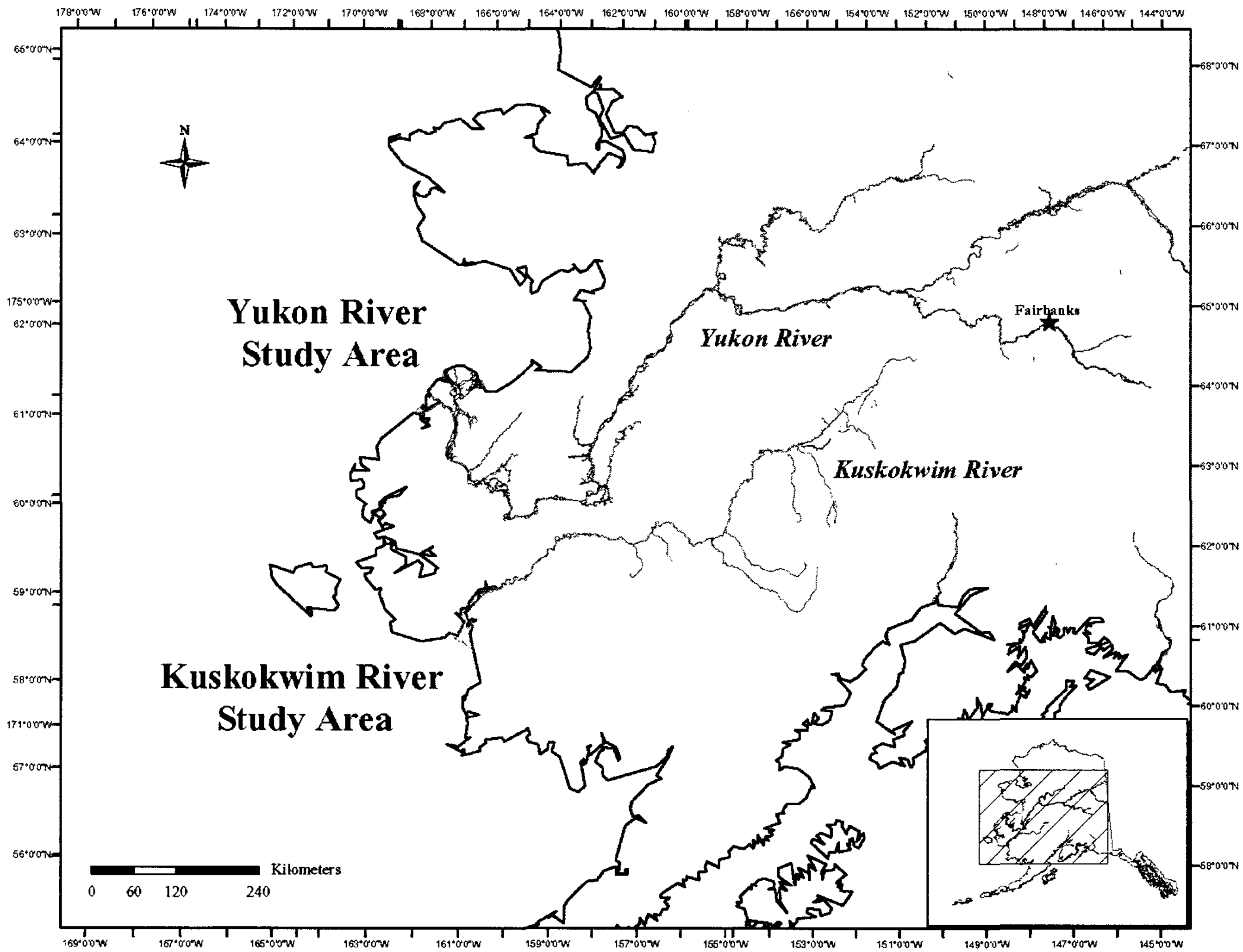
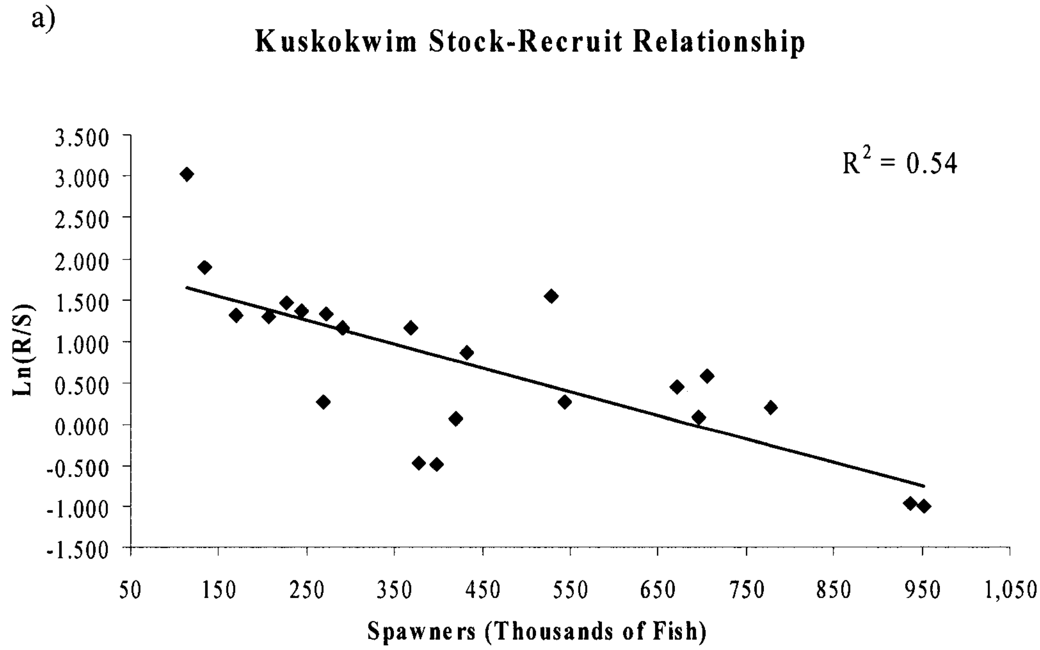


Figure 3.1. Study area for Kuskokwim and Yukon Rivers.

a)



b)

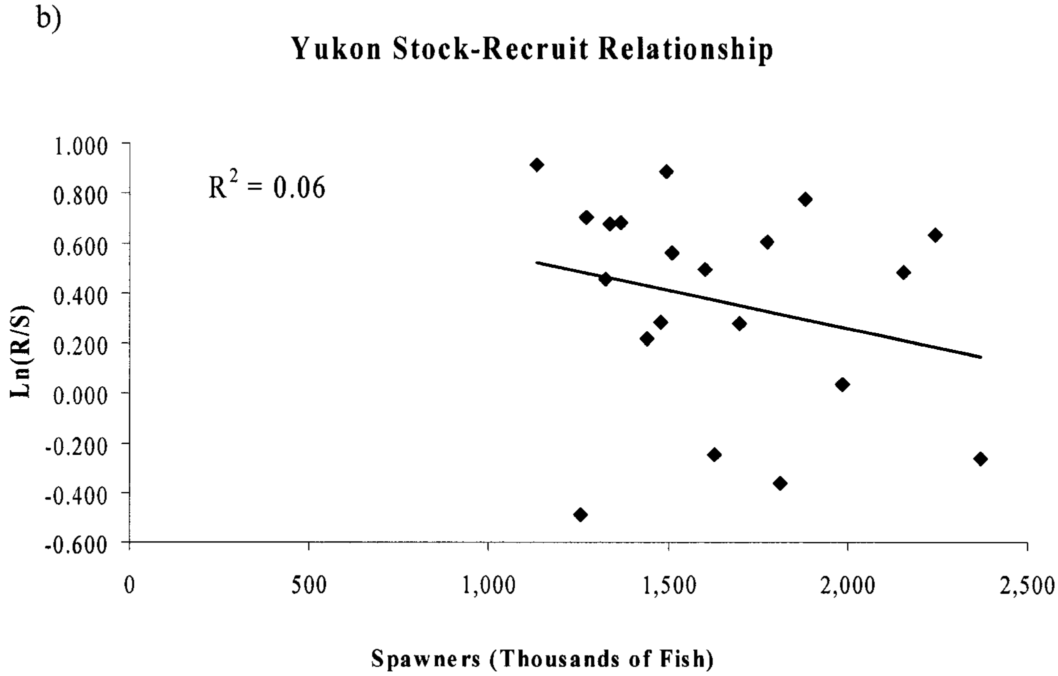
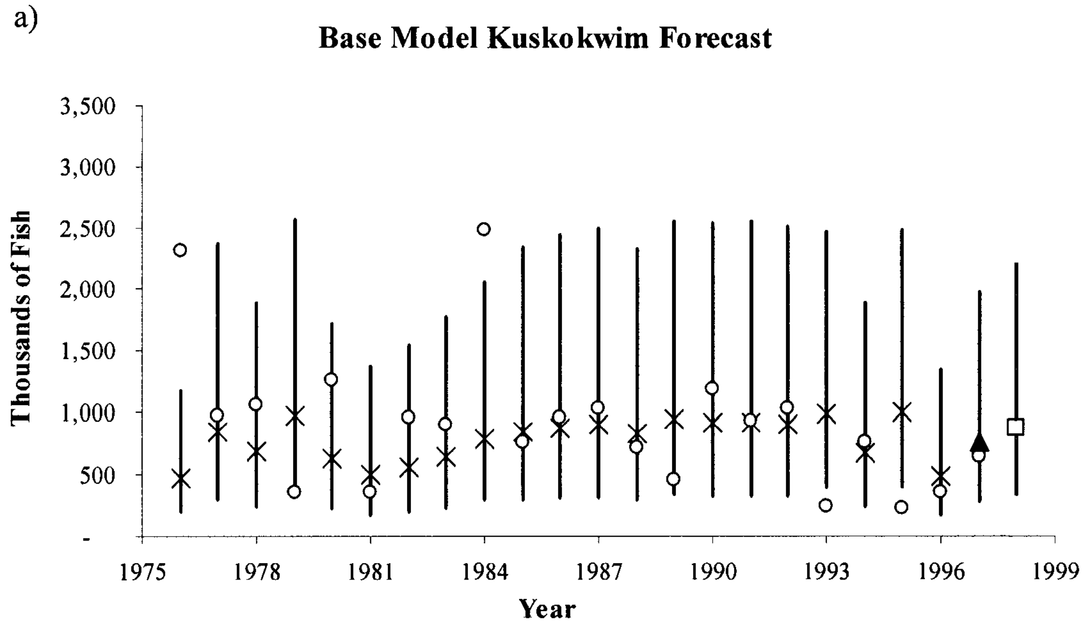


Figure 3.2: Ln(Recruits per Spawner) base model for Kuskokwim (a) and Yukon (b) River. Trendline included is simple-linear regression, equation 1, with no environmental prediction.

a)



b)

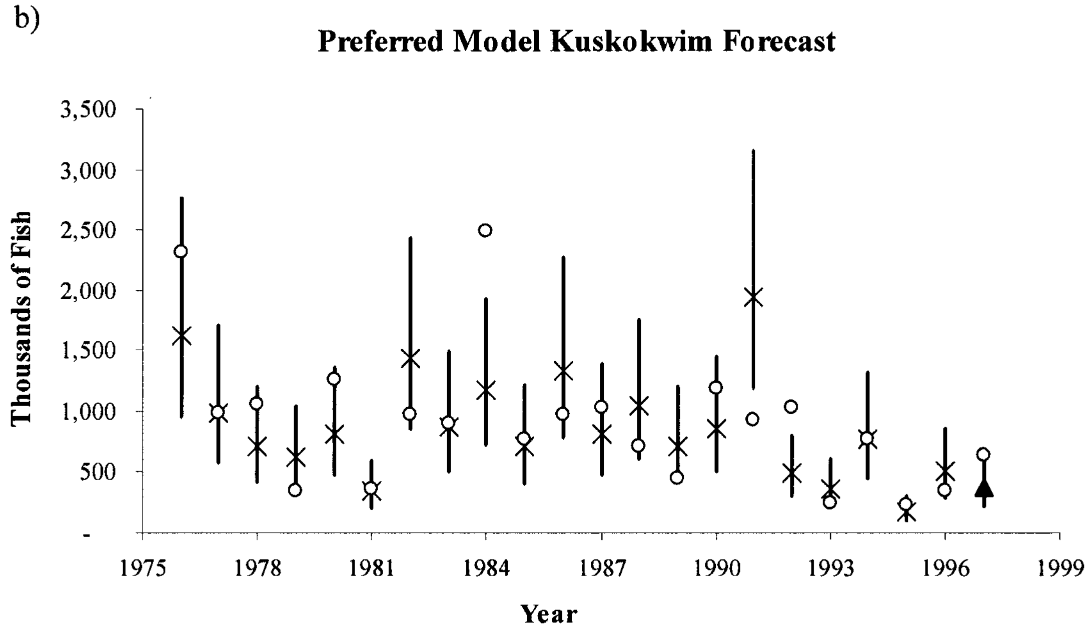
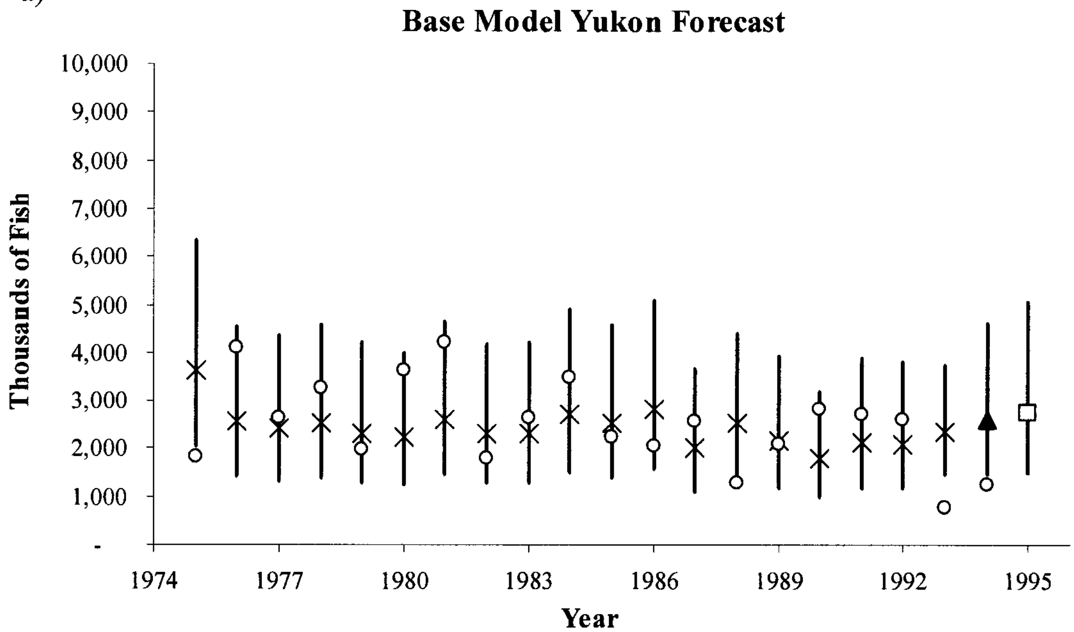


Figure 3.3: Kuskokwim forecasts of recruits with predictions based on leave-one-out cross validation technique. Eighty percent forecast error confidence intervals are provided for both the base model (a) and best model (b). Crosses are the predictions, circles are the observations, and triangles are predictions for an observed year without using that year of data in the cross-validation. Squares for the base model are predictions for the unobserved year.

a)



b)

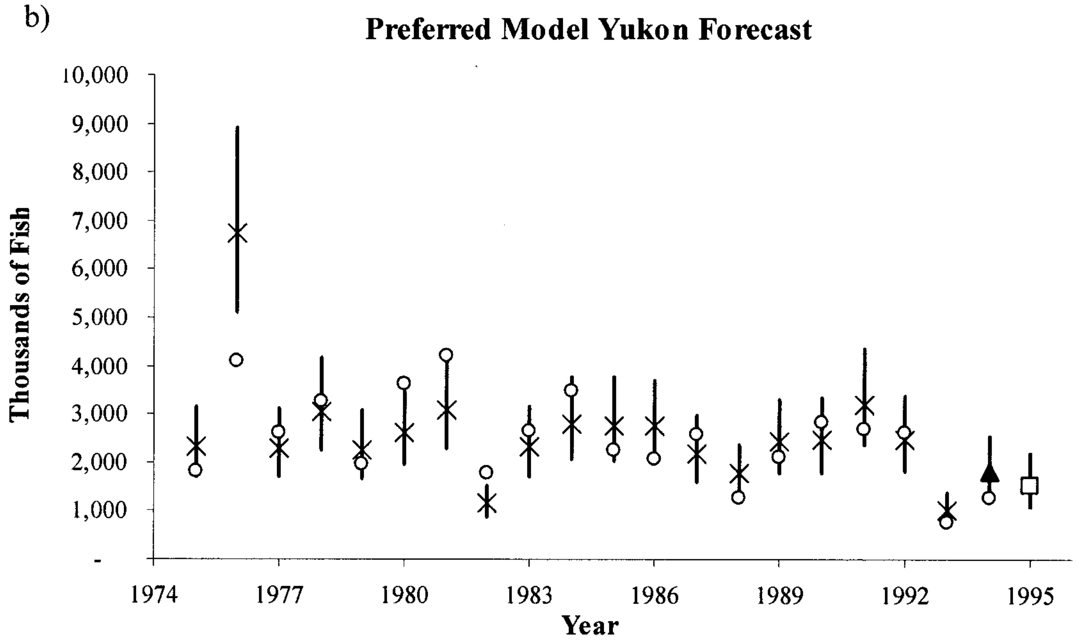


Figure 3.4: Yukon forecasts of recruits with predictions based on leave-one-out cross validation technique. Eighty percent forecast error confidence intervals are provided for both the base model (a) and best model (b). Crosses are the predictions, circles are the observations, and triangles are predictions for an observed year without using that year of data in the cross-validation. Squares are predictions for the unobserved year.

Table 3.1: First stage environmental variables for both rivers. Categories are the five major periods of survival, variables are the types of information we acquired, locations are the areas where data was obtained, names are the acronyms for each variable, months are the months which we averaged data or over which the index was based (J=January, F=February, etc.), lag was the number of years a particular index was lagged from the spawner-recruit data, and sign was the direction of correlations between the variables and the residuals from the base model in both regions (Kuskokwim, then Yukon; N=negative, P=positive, ~ = slightly, 0=none). Sources are provided with subscripts in the variables column and listed after the table. Subscripts following the acronyms indicate a variable eliminated in the exploratory phase, K = eliminated for Kuskokwim, Y = eliminated for Yukon.

Category	Variable	Locations	Name	Months	Lag	Sign
Freshwater	Air Temperature[1]	Bethel, Tanana, and Nome Station	ATPF	AM	+1	N
			ATSR	JJ	+4	N
			ATNF	JJAS	+1	P
	Precipitation[1]	Bethel, Tanana, and Nome Station	PRPF $_{K}$	AM	+1	~P,P
			PRSF $_{Y}$	JJAS	+1	N,0
	Streamflow[2]	Crooked Creek, Pilot Station, and Tanana	STPF	AM	+1	N
			STSR	JJ	+4	P
	Iceout Yukon[3]	Yukon Delta	IYDA $_{Y}$	Date	+1	P,0
Early Marine Residence	Winter Surface Air Temperature[4]	St. Paul Island	SATF $_{K}$	DJFM	+1	0,P
			SATS	DJFM	+2	P
	Favorable Winds[4]	Mooring 2 57°N 164°W	FWMF $_{Y}$	MJJ	+1	N,~N
			FWMS $_{K,Y}$	MJJ	+2	0,0
	Strong Winds[4]	Mooring 2 57°N 164°W	SWMF	MJJ	+1	0,P
			SWMS $_{K}$	MJJ	+2	P
	Along-peninsula component of wind stress[4]	Unimak Pass 54°N 165°W	WUPWF $_{Y}$	NDJFMA	+1	P,0
			WUPWS $_{K,Y}$		+2	~P
			WUPSF $_{Y}$	MJ	+1	N,~P
			WUPSS $_{Y}$		+2	P,~P
	Sea Level Pressure[4]	Bering Sea 55°-65°N, 170°-160°W	SLP $_{K,Y}$	AMJ	+1	0,0
	Ocean Sea Ice Cover[4]	Bering Sea, Various	ICF $_{K}$	Winter	+1	~P,N
			ICS	Winter	+2	N
	Sea Surface Temperature[4, 5]	Mooring 2, Bering Sea	MSSTF	JFMA	+1	P
			ERSSTF $_{Y}$	MJ	+1	N,~N
	Zooplankton[4]	Bering Sea	ZOOP $_{K,Y}$	JJ	+1	0
Early Marine Predators	Western Alaska Coho[6]	Kuskokwim, Delta Rivers	WAKCF	Season	+1	N
			WAKCJ $_{Y}$	Season	-1	N,0

Table 3.1: Continued

Category	Variable	Locations	Name	Months	Lag	Sign
Open-Ocean	Arctic Oscillation[7]	North of 20°N	AOWF	DJF	+1	N
			AOSF	JJAS	+1	N
	Pacific Decadal Oscillation[4]	North of 20°N	$PDOWF_{K,Y}$	DJF	+1	~P
			PDOWR	DJF	+4	P
	Siberian-Alaskan Index[4]	Siberia, Alaska-Yukon	$SAIF_{K,Y}$	DJFM	+1	~P, ~N
			SAIS	DJFM	+2	N
Open-Ocean Competition	Japanese Chum Salmon[8]	Japan Harvest	ACS	Season	+2	N
			ACD		+3	N
			ACR_{Y}		+4	N,~N
	Japanese Pink Salmon[8]	Japan Harvest	APS	Season	+2	P,0

1.) Western Regional Climate Center, U.S. Historical Climate Summaries: http://www.wrcc.dri.edu/climsum.html
2.) U. S. Geological Survey, Water Resources: http://nwis.waterdata.usgs.gov/nwis
3.) Bergstrom, D. J., K. C. Schultz, V. Golembeski, B. M. Borba, D. Huttunen, L. H. Barton, T. L. Lingnau, R. R. Holder, J. S. Hayes, K. R. Boeck, and W. H. Busher. 2001. Annual management report Yukon and northern areas, 1999. Alaska Department of Fish and Game, Commercial Fisheries Division, Regional Information Report 3A01-01, Anchorage.
4.) Bering Sea Climate Page: http://www.beringclimate.noaa.gov/
5.) International Research Center for Climate Prediction, Data Library: NOAA-ERRST dataset (get info at night)
6.) Burkey, C., Jr., M. Coffing, J. Estensen, R. L. Fisher, and D. B. Molyneaux. 2002. Annual management report for the subsistence and commercial fisheries of the Kuskokwim Area, 2001. Alaska Department of Fish and Game, Commercial Fisheries Division, Regional Information Report 3A02-53, Anchorage.
7.) NOAA, National Weather Service, Climate Prediction Center: http://www.cpc.ncep.noaa.gov/products/precip/CWlink/daily_ao_index/ao_index.html
8.) INPFC, NPAFC Statistical Yearbooks: 1975 to 1998, Statistics page: 1999 to 2001, http://www.npafc.org/

Table 3.2: Change in AIC_c from the lowest (best) AIC_c value (Δ AIC_c) for both rivers with the corresponding name of the variables included in each model.

Models	Δ AIC_c	Variables				
Kuskokwim						
Base	20.76					
1 (Best)	0	ATPF	WUPSF	WAKCF		
2	2.88	ATPF	WUPSF	WAKCF	AOWF	
3	0.50	ATPF	WUPSF	WAKCF	AOSF	
4	2.77	ATPF	WUPSF	WAKCF	PDOWR	
5	2.35	ATPF	WUPSF	WAKCF	ACS	
6	2.45	ATPF	SATS	WUPSF	WAKCF	
7	1.39	ATPF	SWMS	WUPSF	WAKCF	
8	2.65	ATPF	WUPWF	WUPSF	WAKCF	
9	2.86	ATPF	WUPSF	WUPSS	WAKCF	
10	1.58	ATPF	WUPSF	MSSTF	WAKCF	
11	2.56	ATPF	WUPWF	WUPSF	WAKCF	AOSF
Yukon						
Base	20.74					
1 (Best)	0	PRPF	SWMF	AOSF		
2	0.83	PRPF	SWMF	AOSF	ACS	
3	2.77	PRPF	ICF	AOSF	ACS	
4	2.78	PRPF	SWMF	AOSF	APS	

Table 3.3: Parameter estimates with corresponding standard errors and P-values for both rivers by competing model. Eleven models for the Kuskokwim and four models for the Yukon. Asterisks denote significant values (P-value < 0.05). Model 1 is the preferred model for both systems.

Kuskokwim Parameters	Estimates											
	Base	model 1	model 2	model 3	model 4	model 5	model 6	model 7	model 8	model 9	model 10	model 11
ln(α)	1.96	2.48	2.47	2.40	2.48	2.41	2.38	2.35	2.50	2.48	2.48	2.41
- β	-2.8 E-06	-3.6 E-06	-3.5 E-06	-3.4 E-06	-3.6 E-06	-3.4 E-06	-3.4 E-06	-3.4 E-06	-3.6 E-06	-3.6 E-06	-3.7 E-06	-3.4 E-06
ATPF (1)		-0.40	-0.37	-0.39	-0.38	-0.36	-0.39	-0.35	-0.36	-0.39	-0.37	-0.35
SATS (2)							0.13					
SWMS (3)								0.14				
WUPWF (4)									0.10			0.12
WUPSF (5)		-0.41	-0.44	-0.41	-0.40	-0.41	-0.39	-0.34	-0.43	-0.37	-0.41	-0.44
WUPSS (6)										0.09		
MSSTF (7)											0.18	
WAKCF (8)		-0.54	-0.52	-0.47	-0.52	-0.43	-0.51	-0.46	-0.51	-0.50	-0.49	-0.44
AOWF (9)			-0.13									
AOSF (10)				-0.27								-0.30
PDOWR (11)					0.09							
ACS (12)						-0.14						

Table 3.3: Continued

Kuskokwim Parameters	Standard Error											
	Base	model 1	model 2	model 3	model 4	model 5	model 6	model 7	model 8	model 9	model 10	model 11
ln(α)	0.298	0.199	0.198	0.193	0.197	0.203	0.213	0.210	0.197	0.198	0.192	0.186
- β	5.9 E-07	3.7 E-07	3.7 E-07	3.6 E-07	3.7 E-07	3.8 E-07	3.9 E-07	3.9 E-07	3.7 E-07	3.7 E-07	3.7 E-07	3.5 E-07
ATPF (1)		0.090	0.092	0.085	0.090	0.093	0.088	0.092	0.093	0.089	0.088	0.086
SATS (2)							0.110					
SWMS (3)								0.092				
WUPWF (4)									0.087			0.080
WUPSF (5)		0.090	0.095	0.085	0.090	0.088	0.090	0.097	0.092	0.094	0.087	0.085
WUPSS (6)										0.086		
MSSTF (7)											0.118	
WAKCF (8)		0.096	0.097	0.097	0.097	0.130	0.098	0.105	0.098	0.101	0.097	0.097
AOWF (9)			0.122									
AOSF (10)				0.154								0.150
PDOWR (11)					0.083							
ACS (12)						0.115						

Table 3.3: Continued

Kuskokwim Parameters	P-value (>[t])											
	Base	model 1	model 2	model 3	model 4	model 5	model 6	model 7	model 8	model 9	model 10	model 11
ln(α)	2.0 E-06*	5.4 E-10*	1.2 E-09*	1.2 E-09*	1.1 E-09*	2.3 E-09*	5.6 E-09*	5.4 E-09*	9.4 E-10*	1.1 E-09*	7.2 E-10*	1.5 E-09*
- β	9.9 E-05*	3.1 E-08*	5.9 E-08*	6.2 E-08*	4.5 E-08*	1.2 E-07*	1.4 E-07*	2.0 E-07*	4.3 E-08*	4.5 E-08*	2.8 E-08*	6.4 E-08*
ATPF (1)		3.8 E-04*	9.6 E-04*	2.6 E-04*	5.7 E-04*	1.4 E-03*	4.1 E-04*	1.7 E-03*	1.3 E-03*	4.5 E-04*	6.0 E-04*	8.8 E-04*
SATS (2)							0.240					
SWMS (3)								0.145				
WUPWF (4)									0.266			0.159
WUPSF (5)		3.0 E-04*	2.8 E-04*	1.8 E-04*	4.1 E-04*	2.9 E-04*	5.7 E-04*	3.1 E-03*	2.4 E-04*	1.1 E-03*	2.2 E-04*	9.9 E-05*
WUPSS (6)										0.298		
MSSTF (7)											0.158	
WAKCF (8)		3.4 E-05*	6.2 E-05*	1.7 E-04*	6.4 E-05*	4.8 E-03*	9.3 E-05*	4.9 E-04*	8.2 E-05*	1.5 E-04*	1.1 E-04*	4.0 E-04*
AOWF (9)			0.301									
AOSF (10)				0.097								0.065
PDOWR (11)					0.283							
ACS (12)						0.229						

Table 3.3: Continued

Yukon Parameters	Estimates				
	Base	model 1	model 2	model 3	model 4
ln(α)	0.858	1.522	1.608	1.633	1.633
- β	-3E-07	-7E-07	-7.6E-07	-7.8E-07	-7.7E-07
PRPF		0.422	0.371	0.394	0.429
SWMF		0.145	0.119		0.162
ICF				-0.118	
AOSF		-0.484	-0.438	-0.477	-0.460
ACS			-0.095	-0.114	
APS					0.096

Yukon Parameters	Standard Error				
	Base	model 1	model 2	model 3	model 4
ln(α)	0.467	0.249	0.238	0.251	0.261
- β	2.79E-07	1.49E-07	1.43E-07	1.51E-07	1.57E-07
PRPF		0.084	0.084	0.090	0.083
SWMF		0.047	0.047		0.048
ICF				0.055	
AOSF		0.094	0.092	0.098	0.095
ACS			0.054	0.055	
APS					0.077

Yukon Parameters	P-value (>[t])				
	Base	model 1	model 2	model 3	model 4
ln(α)	0.082	2.0E-05*	9.3E-06*	1.4E-05*	2.1E-05*
- β	0.29465	2.8E-04*	1.1E-04*	1.4E-04*	2.2E-04*
PRPF		1.6E-04*	5.7E-04*	6.0E-04*	1.4E-04*
SWMF		7.4E-03*	2.3E-02*		4.6E-03*
ICF				0.050*	
AOSF		1.2E-04*	3.0E-04*	2.4E-04*	2.5E-04*
ACS			0.099	0.056	
APS					0.235

Table 3.4: Autocorrelation in data and residuals of competing models. Standard autocorrelation function plots show 95% confidence limits. Autocorrelation is significant at a particular lag if value of autocorrelation function is larger than confidence limits in either positive or negative direction. Slight autocorrelation implies value that is near but does not exceed confidence limit. Number next to positive or negative indicates lag.

Autocorrelation	Significant	Slight
Kuskokwim		
Variable		
ln(R/S)		Positive 1, Negative 5
S	Negative 5	
WAKCF		Positive 2
AOWF		Positive 1
AOSF		Negative 4
ACS	Positive 1 and 2	
Model		
Base		Positive 2
1 - 7	Negative 1	
8		Negative 1
9 - 11	Negative 1	
Yukon		
Variable		
SWMF		Negative 2
ACS	Positive 1	Positive 2
APS	Positive 2	
Model		
2		Negative 5
3		Negative 5
15		Positive 3, Negative 5

Table 3.5: R^2 values for both rivers. We also report the percentage increase from the base model R^2 and from the best model for higher parameter models.

Model	R^2	|>| (%) of Base	|>| (%) of Best	Variables
		Kuskokwim		
Base	0.539			S
1 (Best)	0.888	34.8		S,1,5,8
2	0.895	35.6	0.7	S,1,5,8,9
3	0.906	36.6	1.8	S,1,5,8,10
4	0.896	35.6	0.8	S,1,5,8,11
5	0.898	35.8	1.0	S,1,5,8,12
6	0.897	35.8	1.0	S,1,2,5,8
7	0.902	36.3	1.4	S,1,3,5,8
8	0.896	35.7	0.9	S,1,4,5,8
9	0.895	35.6	0.8	S,1,5,6,8
10	0.901	36.2	1.4	S,1,5,7,8
11	0.918	37.8	3.0	S,1,4,5,8,10
Sub-12	0.634	9.5		S,1
Sub-13	0.566	2.7		S,5
Sub-14	0.663	12.3		S,8
Sub-15	0.759	21.9		S,8,5
Sub-16	0.752	21.3		S,8,1
Sub-17	0.683	14.3		S,5,1
		Yukon		
Base	0.061			S
1 (Best)	0.808	74.7		S,1,2,4
2	0.843	78.2	3.5	S,1,2,4,5
3	0.827	76.6	1.9	S,1,3,4,5
4	0.827	76.6	1.9	S,1,2,4,6
Sub-5	0.283	22.3		S,1
Sub-6	0.255	19.4		S,2
Sub-7	0.343	28.2		S,4
Sub-8	0.403	34.2		S,5
Sub-9	0.685	62.4		S,4,1
Sub-10	0.486	42.5		S,4,2
Sub-11	0.566	50.5		S,4,5
Sub-12	0.468	40.7		S,1,2
Sub-13	0.507	44.6		S,1,5
Sub-14	0.469	40.8		S,2,5
Sub-15	0.770	70.9		S,4,1,5
Sub-16	0.623	56.2		S,4,2,5
Sub-17	0.587	52.6		S,1,2,5

Table 3.6: Cross validation forecast error (CVFE) by river with leave-one-out technique. Top table is the CVFE for each model using all years except the final observed year. Bottom table is the CVFE for each model using all years of data.

Kuskokwim

Model	$\sqrt{(MSE_{1997})}$	Predicted R_{1997}	LC	UC	Real	In Bounds
Base	0.721	758,375	291,029	1,976,201	636,728	Y
(1)Best	0.413	370,842	213,406	644,422	636,728	Y
2	0.401	316,890	185,170	542,309	636,728	N
3	0.393	399,518	235,783	676,957	636,728	Y
4	0.422	389,628	221,254	686,134	636,728	Y
5	0.427	283,218	159,804	501,942	636,728	N
6	0.410	337,078	194,511	584,137	636,728	N
7	0.374	314,707	190,532	519,811	636,728	N
8	0.421	403,249	229,415	708,803	636,728	Y
9	0.432	350,762	196,656	625,631	636,728	N
10	0.362	283,526	174,484	460,712	636,728	N
11	0.391	447,561	264,370	757,692	636,728	Y

Model	$\sqrt{(MSE_{1998})}$	Predicted R_{1998}	LC	UC
Base	0.702	869,777	343,084	2,205,034
(1) Best	0.411	4,755,159	2,749,981	8,222,433
2	0.420	4,394,354	2,508,108	7,699,168
3	0.388	4,199,682	2,498,955	7,057,880
4	0.410	4,215,711	2,437,878	7,290,035
5	0.438	4,069,437	2,265,136	7,310,961
6	0.416	3,814,247	2,187,624	6,650,355
7	0.396	3,369,229	1,984,499	5,720,186
8	0.407	5,102,266	2,959,384	8,796,803
9	0.435	4,113,894	2,299,761	7,359,081
10	0.408	3,830,531	2,220,180	6,608,908
11	0.374	4,512,247	2,733,790	7,447,672

Yukon

Model	$\sqrt{(MSE_{1994})}$	Predicted R_{1994}	LC	UC	Real	In Bounds
Base	0.435	2,591,596	1,451,840	4,626,110	1,259,268	N
(1)Best	0.253	1,811,163	1,288,962	2,544,924	1,259,268	N
2	0.260	1,715,569	1,207,520	2,437,375	1,259,268	Y
3	0.281	1,872,524	1,281,771	2,735,548	1,259,268	N
4	0.263	1,873,807	1,313,854	2,672,408	1,259,268	N

Model	$\sqrt{(MSE_{1995})}$	Predicted R_{1995}	LC	UC
Base	0.452	2,763,291	1,513,909	5,043,751
(1) Best	0.253	1,537,794	1,095,650	2,158,364
2	0.264	1,339,081	938,822	1,909,985
3	0.274	1,267,970	876,739	1,833,780
4	0.263	1,533,237	1,076,350	2,184,063

General Conclusions

Our modeling framework allowed for the incorporation of multiple data sources to successfully generate population estimates for a data-limited situation. We developed estimates of total abundance and escapement for the Kuskokwim and Yukon River drainages using diverse escapement indices, annual and weekly commercial catch and effort, subsistence harvests, test-fish CPUE and whole river sonar enumeration. Additionally, we determined that PCA effectively summarized tributary escapement data for large rivers such as the Yukon and that an independent assessment of abundance was necessary for our model. Error estimates of the time series of abundance and escapement as well as of the model parameters were generated by bootstrap methods.

An important application of the escapement index estimated by PCA is the identification of a trend that extends over the entire basin, suggesting the influence of a large-scale forcing agent on summer chum salmon survival. We can surmise that because this pattern explained a large amount of variation in the escapement data over a vast geographic area, a major source of mortality occurs when the fish are in a common environment (e.g., early marine environment, open-ocean). This association provides good support for the inclusion of environment predictor variables in a spawner-recruit relationship developed from these estimates.

Several assumptions were required for this modeling approach. We considered only fixed model parameters such as the catchability coefficient and scalars on the test-fish CPUE. These measures may not adequately capture aspects of the commercial or test fishery that change from year to year such as gear efficiency or changes in behavior of fish. Bootstrap coefficients of variation (CV) about the model parameters reflect some of these concerns and the weighting scheme provides some regulation of the relative influence from each dataset on the estimates as reflects our confidence in the data. However, these error estimates demonstrate the error on each parameter due to the modeling process and not the potential measurement error about the empirical data used in the model. We considered the potential influence of this measurement error through simulations on a similar system with known abundance and escapement information.

We used sockeye salmon data from the Ugashik River, Bristol Bay to test the effects of measurement error on the estimation process. We applied the same statistical framework of our previous modeling technique to determine whether this process could reproduce the true population estimates and parameters. We then simulated various reported levels of measurement error on the escapement index and sonar data. Performance measures of bias and accuracy were calculated over twenty measurement error scenarios. Increases in error on abundance data had negligible effect on all estimates and abundance estimation was fairly robust to all error scenarios. Escapement estimation was highly confounded with the particular three-year combination of abundance years that we used to emulate sonar data. Good combinations exhibited improvements in escapement estimation under high levels of simulated escapement measurement error. Poor combinations produced highly biased escapement estimates. Effort data were fairly limited in our known system resulting in different interpretations over the time series and poor performance when the model relied more on the catch and effort data. Specific properties of the three-year abundance combinations that produced good versus poor estimates were difficult to identify; however, abundance estimates with good contrast between years and good agreement between run timing of associated catch and effort data may alleviate the dependence on abundance combination. A full simulation may better identify particular caveats of measurement error within each of the potential datasets used in this modeling framework. It is imperative that managers consider the quality of the additional data sources used in our modeling framework and develop appropriate weighting schemes that reflect their confidence in the data.

Given these considerations, we then used age data from the Kuskokwim and Yukon Rivers to create estimates of spawners and recruits by brood year from the abundance and escapement data. Rigorous model-development and selection were applied to potential environmental variables to create "best" models for the Kuskokwim and Yukon Rivers that explained 89% and 81% of the variability in survival rates, respectively. These are good improvements over the base models with no environmental information, which explained 54% of the variability in the Kuskokwim and only 6% in the Yukon. The models were developed using a process that focused on biological realism between recruitment and environmental conditions. The increases in explanatory power suggest that adding environmental variables to the stock-recruitment relationships of summer chum salmon in these two river systems may dramatically improve future forecasts of recruitment.

An important application of the environmental models is that they help explain the lowered survival of the past few years much more than the base spawner-recruit model. The direction of all parameter estimates for the environmental variables made biological sense and recent changes in these variables were consistent with current anomalous conditions in the Bering Sea. Finally, estimates of forecasting error on the best models contained tighter bounds about the point estimates than the error on the base models. Therefore, the inclusion of environmental variables in our modeling process allowed for a better understanding of the stock-recruitment dynamics and improved forecasting in this region.

This novel modeling approach to data-limited situations of Pacific salmon was successful in developing the necessary population estimates, assessing some potential caveats due to uncertainty in the data, and selecting appropriately defined environmental variables for quantitative stock-recruitment analysis and forecasting. We recommend that managers applying this procedure consider the assumptions inherent in the model and be particularly aware of the potential sources of measurement error on the empirical data. At a minimum, managers may consider the simple trends in the key environmental variables to formulate some idea of potential fluctuations in returns from year to year and use this information when setting escapement goals or harvest strategies. In data-limited situations like the Kuskokwim and Yukon Rivers, our modeling process creates a statistical framework that aids fishery managers in understanding current trends and reveals potential mechanisms involved in these events.

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